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Cognitve Load Estimation in Drivers for Advanced Driver Assistance System

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COGNITIVE LOAD ESTIMATION IN DRIVERS FOR ADVANCED DRIVER ASSISTANCE SYSTEM

by

Priyadharshini Ramakrishnan

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Declaration of Co-Authorship / Previous Publication

Co-Authorship

I hereby declare that this thesis incorporates material that is result of joint research, as follows: Chapters 2 of this thesis was co-authored with Dr.Balasingam, and Dr.Biondi who provided supervision and guidance during the research and writing process. In all cases, the key ideas, primary contributions, experimental designs, data analysis, interpretation, and writing were performed by the author.

I am aware of the University of Windsor Senate Policy on Authorship and I certify that I have properly acknowledged the contribution of other researchers to my thesis, and have obtained written permission from each of the co-author(s) to include the above material(s) in my thesis.

Previous Publication

This thesis includes one original book chapter that have been previously published/submitted for publication in peer reviewed journals, as follows:

Thesis chapter	Publication title/Citation	Publication status
2	Ramakrishnan, Priyadharshini, Balasingam, Balakumar, Biondi, Francesco (2020),Cognitive Load Estimation for Adaptive Human-Machine System Automation	Under review
–	Ramakrishnan, Priyadharshini, Balasingam, Balakumar, Cognitive Load Estimation for ADAS	Yet to submit

General

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Abstract

In this thesis, we investigate some physiological metrics to estimate the cognitive load experienced by drivers in a driving simulated environment and how their cognitive load is varies and affects certain physiological metrics.It is important to better understand the cognitive status of the human beings inorder to design efficient machines for automation. For instance, an advanced driver assistance system (ADAS) with the ability to understand the cognitive state of human will enhance the overall safety of the roads. In order to achieve such an intelligent automation system involving humans we need to develop approaches that can better estimate cognitive load through non-invasive means and to develop control strategies for real-time system adaptation with humans. The focus of this thesis is to present some hypotheses for cognitive load estimation based on some physiological measures, such as, pupil diameter, heart rate, and response-time and how each of these metrics change for varying cognitive difficulty levels. The variation in these metrics is proved using statistical analysis techniques.

Acknowledgement

Firstly, I would like to gratefully acknowledge the unyielding support and mentorship offered by my supervisors- Dr. B Balasingam and Dr. F. Biondi. Their profuse knowledge in this field of research and their willingness to provide consistent inputs helped in the timely completion of my coursework. I am grateful to have spent time in their tutelage. Without their expert guidance and persistent help, this dissertation would not have been possible.

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Chapter 1

Introduction

In this thesis, the author explores the research and development of technology in the realm of cognitive load estimation and how it affects the physiological factors in a driving simulated environment. The author presents this as a collection of the previously submitted work. Cognitive load estimation in itself is a broad and diverse topic which has an increasing number of practical applications not only in Advanced Driver Assistance System but also in manufacturing, aviation and Virtual Reality and so on. One interesting application of cognitive load estimation, which has drawn a lot of attention for a long time now is its estimation through physiological measures, and this thesis is also based on studying the variation in the physiological metrics, for tasks with varying cognitive difficulty levels when driving.

A study to estimate the cognitive load and its variations with physiological measures in a real-time driving environment will be very interesting to perform, this thesis and the experiment performed in this study is seen as a step closer towards the afore mentioned study. With the advent in the field of technology, physiological data can be obtained with unprecedented accuracy, but such hardware is still expensive and unlikely for general public use. Readily accessible hardware, such as simple camera eye-trackers, simple 3 lead ECG, and driving simulator gives the investigator freedom to move naturally and are more affordable than their expensive counterparts. The author has tried to interpret the physiological measures collected when performing the driving task in the best way possible and estimate the cognitive load experienced by the subjects when performing the task.

1.1 Organization of the Thesis

The author has elected to present this thesis structured according to the manuscript format rather than the traditional format. That is, the chapters to follow consist of manuscripts previously written and submitted by the author, with first authorship. As prescribed by the manuscript format, abstracts have been omitted. It is the belief of the author that by virtue of the chosen format their thought process, understanding of the research topic and its place in the modern world, and journey toward producing increasingly meaningful contributions, are far more accurately conveyed as a story told through a collection of chronological works.

While a traditional thesis commonly contains a general literature review and problem statement, the author has chosen to forego these sections in the traditional sense. The reader will find that each of the manuscript chapters provide their own introductions which serve the purpose of familiarizing the reader with both the context of the research and relevant literature. Each of the manuscript chapters also contain a section describing the problem to be addressed by the research. To include a general literature review and problem statement in this thesis would be to introduce unnecessary redundancy. It must be noted, however, that some amount of redundancy will persist throughout the manuscript chapters as a consequence of each being originally written as their own, standalone entities.

The remainder of this thesis is organized as follows: Chapter 2 gives an introduction to human machine automation and insight into physiological measures, the different types of physiological measures that exist and how each of these measures can be used to estimate the workload that human being is experiencing when performing a variety of tasks. This chapter also focuses on the recent advancements in cognitive load estimation based on non-invasive measures. The next chapter 3 describes in detail the devices that were used for the purpose of the study discussed in this thesis and how by varying the task load the change in cognitive load can be estimated. The final chapter 4 we will discuss the statistical methods that can be used for the analysis of the data, and how we can better interpret the physiological changes and quantify the variations. The final chapter some inferences from the data and the analysis is made and the drawbacks of this study is also discussed. This thesis concludes with the future scope that exists in this field of research.

Chapter 2

Cognitive Load Estimation for Adaptive Human Machine System Automation

2.1 Introduction

2.1.1 Human-Machine Automation

Human machine system (HMS) is where a human operator's functioning is integrated to that of a machine. The goal of such a system is to enable the human to effectively operate and control the system, whilst the machine provides feedback information and aids in better performance of the operator. When designing a HMS there are a few factors that need to be considered, such as, extent of automation of the HMS, system design, functions that need to be automated, the level of automation and degree of human involvement in a task controlled by the machine [1]. Traditionally these systems have been explored as binary function allocations where either the machine or the human is assigned to a task. Recently intermediate levels of automation have been developed, where the machine performs the task but the human remains engaged in the task, this evades certain out-of-the-loop performance problems [2]. Adaptive automation has been largely proposed as a method for regulating this out-of-the-loop performance problems, specifically in complex control systems [3]. Attentional factors greatly influence the human interaction with the system. The level of automation in the system could be semi-automated or a fully automated system [4]. In today's world there are several applications for a human machine system: aersopace, aviation [5], e-learning, information processing, autonomous driving, assembly operations [6], manufacturing. Past few decades have seen tremendous progress in system automation. System automation can be broadly classified into 4 functions- information acquisition, information analysis, decision selection, and action implementation. A system can include all of these functions, or one or more of them at various levels with varied levels of automation [7]. To enhance the overall HMS performance, the workload on the operator must be assigned keeping in mind the fluctuation of psychophysiological functional status of the operator from time to time [8]. In order to better understand the psychophysiological functional status of the operator, it is important to understand the cognitive load experienced by the human performing the task [9].

Unlike physical load, cognitive load is difficult to measure directly. Researchers have suggested that cognitive load can be measured using analytical and emprical methods [9] [10]. Analytical methods are aimed at evaluating the cognitive load by collecting analytical data with methods such as mathematical models and task analysis. Empirical methods involve estimating the cognitive load by collecting subjective data using rating scales, performance data using primary and secondary task techniques and physiological data using physiological techniques. These techniques are based on the assumption that changes in cognitive functioning are indicated by physiological variables [14]. The monitoring of cognitive load is useful in enhancing the performance on the task. As the task becomes challenging, the amount of resources being used for task completion will also increase [11]. Cognitive load measurement plays a vital role in semi-autonomous vehicles, aviation, manufacturing, surgery, mobile learning interfaces to name a few applications [12] [13].

The Yerkes-Dodson law (YDL) [15] defines an empirical relationship between arousal and performance.This law dictates that the performance increase with arousal but this is true only upto a certain level. When the level of arousal is too high, the performance decreases, and when the arousal is too low, there is loss of interest which results in low performance [15]. In order to achieve maximum performance, the workload has to be in the optimum range — by providing optimum arousal, maximum performance can be achieved [16]. The YDL can be exploited in many practical situations for performance enhancements: affective computing, logic theory, designing e-learning methods, manufacturing, aerospace, cyber-physical systems. The level of arousal plays a vital role as it is directly related to the cognitive state of the subject [17]. There exists several methods to identify the optimum level of arousal and predict when the performance is expected to be the highest.

This law plays a vital role in designing a better HMS that is able to adapt and re-assign tasks based on the cognitive state of the human performing the task [18]. A generic flow diagram of how this system would function is shown in Fig. 2.1. The prediction of workload plays a vital role in understanding the cognitive state of the human and vary the task load. The operational performance of a closed-loop HMS can be enhanced when the machine is able to monitor the operator's cognitive state and adapt accordingly to maximize the effectiveness of the HMS [19]. There exists many techniques of estimating the cognitive workload experienced by the humans; some of which will be discussed in Section 2.2.

2.1.2 Cognitive Load Measures

The basis for designing different levels of human-machine system automation is to understand the cognitive state of the human being [19]. As such, the first step towards designing a better man-machine system is cognitive load estimation — preferably

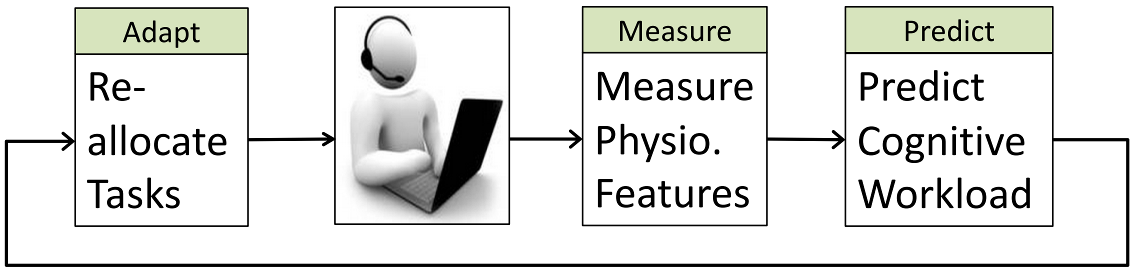


Figure 2.1: **Human-machine automation.** The goal is to keep the human performance at the optimum level by reallocating the tasks.

through non-invasive measures. There are several different techniques for cognitive load measurement as shown in Fig 3 which shows a taxonomy of different approaches to it. Broadly these techniques can be classified into objective and subjective measures of cognitive load. Objective approach to cognitive load estimation are further classified as performance based metrics, physiological metrics, and behavioral metrics. Pupil diameter, eye-gaze patterns, eye-blinks, heart rate, cardiac activity, Electroencephalogram (EEG) activity, event related potential (ERP), and skin conductance are some of the physiological metrics of cognitive workload [20]. Behavioral metrics of cognitive workload include gestures/movements when performing a task that can act as non-verbal outputs of the human body revealing valuable information on how people think and feel [21]. Detection response task (DRT) is a widely accepted standard for a behavioral measure of cognitive load [22]. As the task complexity and task workload or stress increase, the behavior of the human performing the task is said to resort to routine action and reduce the variability in their response to the task as the complexity of the task increases [23]. It would be interesting to understand how committed/engaged the human remains in the task as the task workload increases [24]. Knowledge on how engaged the human is in the task that's underway would help us better understand the cognitive state of the person. The task engagement can be predicted by measuring certain behavioral metrics like their response to visual or tactile stimuli [25]. Pupil diameter (physiological metric) and response time (behavioral metric) are two well established and widely used methods for cognitive load estimation [26]. Subjective measures of cognitive load involves a self-rating approach by the person performing the task to rate the task difficulty on various scales. The NASA task load index (NASA-TLX), a retrospective questionnaire, is one of the well known subjective measures of cognitive load [27].

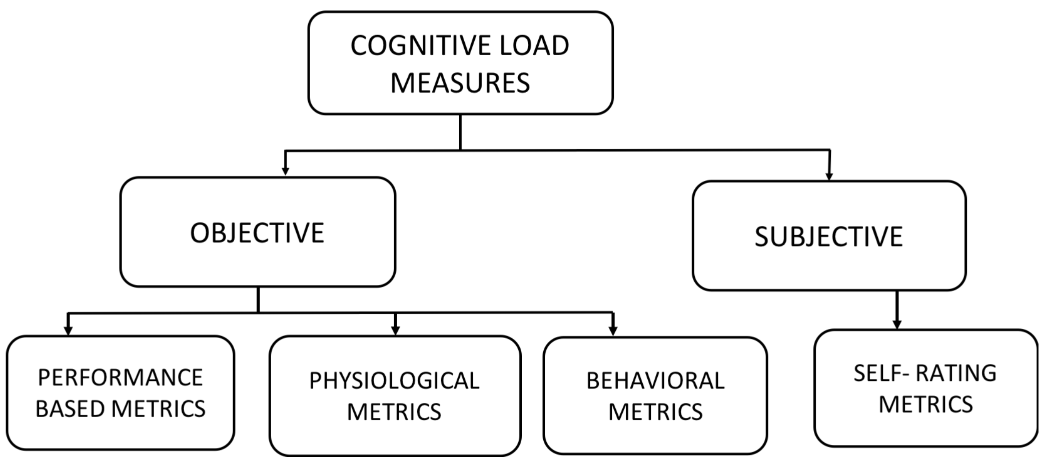


Figure 2.2: **Cognitive Load Measurement Approaches.** The above figure shows the various approaches to cognitive load measurement.

Human physiological signals have been successfully used to indicate the work load during task execution. There exist several techniques to measure the physiological signals some of which are listed in Table 2.1. Although there are several physiological signals that are indicative of the cognitive load, not all of these measures can be reliably used in all applications. Considering the sensitivity, ease of measurement, and usability many of the current methods listed in Table 2.1 are not ideal for ubiquitous applications. This has given way to the increase in number of wearable devices that can measure the attention given to the task, with physiological signals and be able to constantly estimate the mental load experienced by human subjects [37]. However it is not possible to use wearable devices to estimate the work load in all applications [38]. In applications where it is not possible to intervene with the activity being performed whilst measuring the cognitive load, researches have led to the use of non-invasive techniques for estimating the same. Applications where invasive techniques cannot be deployed, non-invasive measure of cognitive load have been soughed to. A few applications where non-invasive measures can be used and how it helps in enhancing the performance of the system is discussed below.

2.1.3 Some Applications

Applications where non-invasive measures need to be deployed include surgery, flight-safety, human-centered design, multi-media learning, to name a few [39]. In driving related environment the non-invasive metrics can be used to estimate the workload experienced by the driver, to enhance the automated features and safety standards [40]. In most of the applications listed non-invasive metrics play a pivotal role in better understanding the cognitive state of the human being.

Technology has grown and diverse teaching techniques have emerged such as e-books, massive online open courses (MOOC), and gamification. Online teaching/learning has become an integral part of education today. Technologies continue to provide revolutionary improvements in traditional learning environments. The pedagogic trend is becoming "student-centered" [41]. The cognitive load theory is an instructional design theory that focuses on designing conditions an principles that enhance learning [42]. The assumptions of this theory is dependent on certain aspects of human cognition. Cognitive load theory assumes that instructional design should address the limitations of working memory which temporarily maintains and stores information [43]. Working memory is the part of human cognition where the central work of multimedia learning takes place [44]. This is due to the fact that working memory processes information before it is stored in long-term memory [45]. Likewise, working memory selects verbal and pictorial information from sensory memory, organizes them, and integrates them with each other [43]. Therefore, one of the basic premises of cognitive load theory is that instructional design for online teaching should optimize cognitive load at a level that does not hinder learning. The point is not to decrease cognitive load but keep it at a level that does not prevent learning [46]. Both cognitive overload and underload do not promote learning. Therefore, it is important to maintain optimum load to design better teaching methodologies and techniques. It is also necessary to keep in mind, the way in which working memory functions which will help us design online learning program and keep the end user engaged in the learning task. Pupil dilation can be used as an index of learning [47]. It is one of the important indicators of the learning that takes place remotely.

Most educational institutions use traditional face-to-face instruction. Many online courses are available in which video lectures are used as a medium of instruction [48]. A video lecture may be more complex, paired with slide presentations, interactive quizzes and demonstrations [49]. Online video lectures have become increasingly common in recent years, as evidenced by their use in many organizations, educational institutions, and open learning systems, such as Coursera, Udemy, TED to name some. Video based learning often provide students with additional time to fully understand classroom course materials by allowing them to review lectures repeatedly [50]. Video based learning is targetted at harnessing learning motivation, increase the learning performance, satisfy individual learning needs with varied learning styles, and select the most appropriate format to facilitate learning [51]. Moreover, attention is said to facilitate the selection of incoming perceptual information and limiting the number of external stimuli processed by the bounded cognitive system to avoid overloading [52]. Importantly learning process without sustained attention lacks effective identification, learning, and memory [53]. Sustained attention to the content is of priority and concern for effective learning, explaining the need to determine whether different styles of video lectures affect sustained attention in video based scenarios. Research studies have asserted that design of multimedia materials or video lectures should consider the affective state (i.e. a learner's emotional state) [54].

The advent of cloud storage and processing, in combination with the advancements in connectivity, has prompted video-on-demand (VoD) as a new form of television. Unlike traditional video streaming devices like television, in VoD, the viewer browses through the lists of available videos and selects one to play; further, the VoD allows the user to pause and resume videos at any time. The content providers, –earlier had the upper hand in deciding what the viewers will watch and when, are now forced to contest for the attention of the viewers; this prompted a new research area called recommendation systems [55] where the *recommender engines* employ algorithms to suggest videos that the users might be interested to watch. Existing recommendation systems rely on behavioral metrics to estimate the quality of experience (QoE) to suggest videos with an objective to keep the QoE of the user at a higher level. It is interesting to note that aspirational VoD system [56] is not so different in structure compared to the conceptual HMS introduced in Fig. 2.1; what is different though is the fact that the present day VoD systems use behavioral metrics, based on browsing history, to make their predictions. Considering that most video systems are able to connect to physiological sensors of a viewer, such as, smart watches video cameras, the future VoD system will be able to exploit physiological measures to provide an entertainment experience that is optimized to physical and mental health of the viewer.

With semi-autonomous vehicles rapidly taking over manually controlled vehicles, the important factors contributing to the changeover are the advanced driver assistance systems (ADAS) which aims to facilitate driving with minimal effort by the human driver. The ADAS based intelligent safety systems could improve road safety in terms of crash avoidance, crash severity mitigation and protection, and automatic post-crash notification of collision [57]. ADAS could be useful as an integrated in-vehicle infrastructure based systems which contribute to all of these crash phases. Crash data studies have found that driver error and other human factors contribute to as much as 93 percent of vehicle crashes [58]. Human error can occur due to lack of training on how to use ADAS, the complexity of ADAS, change of human behavior and sole attention on ADAS rather than primary task of driving. Instead of providing the entire control to the driver, ADAS design which can adapt and trigger based on feedback received from the driver's cognitive state would be a better suited system [59]. To detect drowsiness through the percentage of eye closing data- the number of blinks, through steering mounted camera and depending on the level of drowsiness a warning message can be displayed, or the vehicle can be slowed down and stopped thus avoiding a crash [18]. A method for detecting driver's inattention to facilitate operating mode transitions between driver and driver assistance systems based on cognitive model of human behavior is necessary [60]. Cognitive load delays a driver's response to critical events. Under conditions of high cognitive load, failure of ADAS due to human error can result in undesired incidents such as crashes [61]. The processing, effort, and motor actions also evoke the pupil dilation. Previous studies have shown that the mean and variance of the pupil dilation increases with cognitive difficulty. It was also seen that eye-tracking can be used for detecting and tracking transient changes in the pupil dilation for multiple levels of cognitive difficulty [62]. Short-duration studies involving pupil dilation suggests that when information is received into the memory pupil dilates slightly, dilation increases when the information is processed and constricts when information is retrieved. For the long-duration task, the peak pupillary dilation is consistently higher than the short duration task but the constriction during memory retrieval is almost similar in both the conditions [63]. Pupil dilation is by far the trusted non-invasive metric of cognitive load measurement.

Having explained the application of non-invasive measures of cognitive load, the remainder of this chapter is organized as follows: Section 2.2 details several non-invasive measures of cognitive loads; Section 2.3 details several experiments where one of these non-invasive measures, the pupil diameter, was experimented as a measure of cognitive load.

2.2 Noninvasive Metrics of Cognitive Load

In this section, we discuss some non-invasive measures of cognitive load that are possible candidates to the HMS automation concept shown in Fig. 2.1.

2.2.1 Pupil Diameter

Time bound averaging of pupil dilation data, along with events that induce higher cognitive load is associated with the central nervous system. When people are given cognitively challenging tasks, the pupil dilates; this phenomenon is known as task-evoked pupillary response [64]. Kahneman (1973) in his theory of attention concludes that the primary measure of processing loads can be based out of task evoked pupillary responses [65]. This theory was based on the fact that humans have limited cognitive capacity and this is closely related to the arousal system. Human cognitive processing such as problem solving, language comprehension, are accompanied with pupil dilations. Research show that any sensory movement - tactile, auditory, or gustatory triggers pupil dilation [66]. Although the dilation in pupil might be small, it adds a lot of predictive strength to the cognitive load detection [62]. The pupillary response has long been known to be directly associated with increased mental activity. Despite the challenges in using pupil dilation as a measure of cognitive load, the recent advancements in the field of eye-tracking has made this a feasible tool for human system automation. Today's technology allows to obtain pupil diameter measurements using non-invasive, inexpensive cameras [67]. Pupil dilation can also be used as a method of detecting and tracking transient changes with varied levels of cognitive difficulty. The variation of pupil diameter for short duration and long duration tasks are different. For shorter tasks when the information is received into the memory the pupil dilates; the dilation further increases when the information is being processed and finally constricts when the information is retrieved. For long duration tasks the pupil dilation is different [68]. The peak pupillary dilation is consistently higher in tasks with longer duration, but the constriction in the information retrieval phase is almost similar in both the tasks [66].

2.2.2 Eye-Gaze Patterns

Research on eye-gaze based cognitive load detection dates back to the 18th century when Louis Emile investigated saccadic movement of the eye during a reading task. Changes in the activity of the central nervous system are systematically related to the cognitive processing of the task [69]. Study of eye-gaze patterns not only helps in better understanding of the cognitive load experienced by the person, but it also helps in better designing of billboards, traffic signs, and posters. Eye gaze serves many functions ranging from social, emotional and intellectual [69].

2.2.3 Eye-Blink Patterns

Eye blinks are said to occur before and after a cognitively demanding task has been performed. Pupil dilation and blink patterns provide complementary and mutually exclusive indices of information processing. Though both these parameters are associated in a way with cognitive load measurement, blinks prevent the measurement of pupil diameter to a certain extent, and mostly these two indices are discussed independently in literature [34]. However, there are certain studies that show that blinks occur during the early stages of sensory processing and pupil dilation better reflects sustained information processing. An independent literature suggests that blinks are not a random occurrence but blink bursts follow high cognitive load or information processing. Cognitive processing associated with blinks can be sporadic and a combination of these indices gives us a better understanding of the relationship between cognitive load and blink-occurrence [71].

2.2.4 Heart Rate

The cognitive load experienced by the driver has always been associated with the driver's heart rate. Unlike any other performance measures or subjective workload assessment, the physiological measure allows a continuous assessment throughout a task [72]. These measures do not necessitate any interruption of the primary task, which is advantageous over studies that purely examine only behavioral responses. Measure of cardiac activity for assessing cognitive workload can be done by simply measuring the electrical signals that are emitted by the heart. The cognitive load also depends on whether the secondary task being performed is visual, auditory or haptic [73]. Cardiac activity measurement offers a great deal of advantage over other devices such as EEG, which require a greater deal of training to be used and are more susceptible to noise from the physical movement of the subject. Heart rate monitors are in comparison cheaper, and can be used with minimum training by researchers. The most basic of the cardiac assessment feature is heart-rate (HR), analyzed using the magnitude of a particular cardiac subcomponent deflections (commonly referred to as beats per unit of time) or IBI which measures the beat-to-beat variations. Change in cardiac activity is also affected based on factors that vary from one subject to another. The major contributing factors for this variation are : the skill, knowledge, and previous experience related to the particular task [35].

2.3 Details of Open-Loop Experiments

This section describes the details of some experiments designed to validate the use of eye-tracking metrics as indicators of cognitive workload.

2.3.1 Unmanned Vehicle Operators

Autonomous vehicles have seen significant progress in the recent past. It is important to note that the autonomous features are subjected to continuous development;

however, available autonomous features can be combined with human operators for increased productivity. Fig. 2.3 illustrates such a scenario where the one-operator-to-one-vehicle is replaced by multiple-operator-missions-to-multiple-vehicles. Unmanned aerial systems (UASs) are good examples of this emerging model [74] that will soon find applications in ground-based autonomous vehicles.

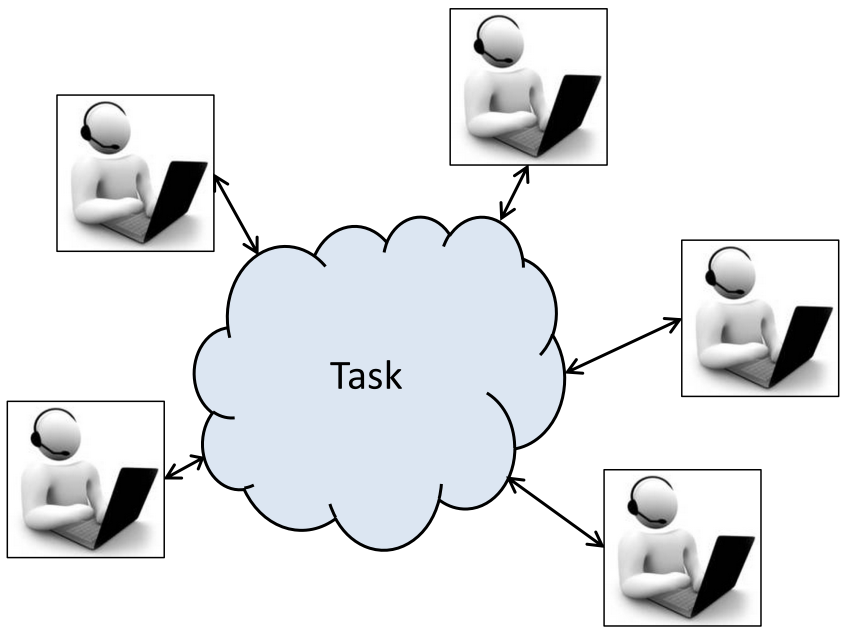


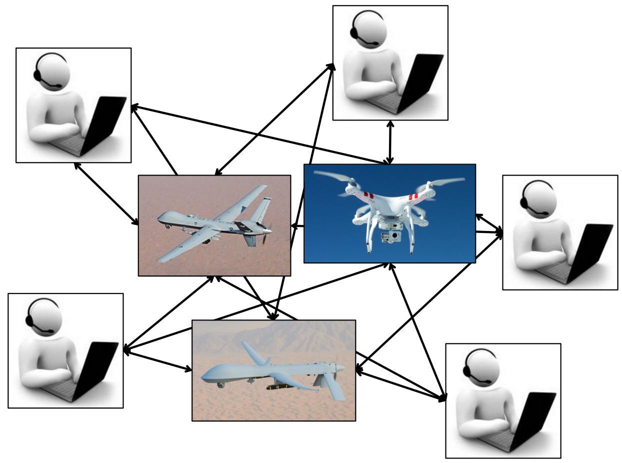
Figure 2.3: **Generic illustration of autonomous vehicle operation.** This figure illustrates how autonomous vehicle operators will be utilized human operators to execute complex missions.

The UASs are becoming ubiquitous in a wide variety of application, such as, military surveillance [74], agriculture [75], and delivery services [76]. Some sophisticated UAS, such as the single camera, 90-minute endurance, RQ-11 Raven and Group 5, 14 hour endurance, MQ-9 Reaper [77], were initially used in defense applications. In recent years, the UAS has found numerous commercial applications.

Figure 2.4(a) depicts a typical UAS operation where numerous operators need to monitor the progress of the UAS operation, e.g., delivery of an item, applying fertilizer, etc., in real time. Even though each UAV is able to operate (fly) without a human pilot in it, the overall mission of a UAS requires the continuous attention of human operators. Each UAS is different and the task demand for each operator varies often resulting in sub-optimal tasking and mission performance; it was asserted that 68% of UAS mishaps in the US defense applications were attributable to human error [78, 79].

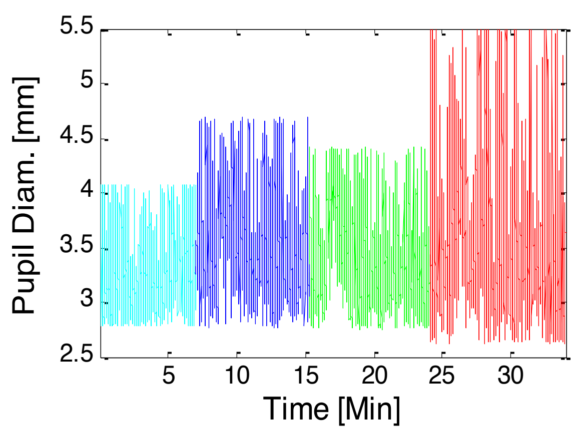
Figure 2.4(b) depicts the experimental set-up used to simulate an UAS operational scenario [80]. The participant monitors the progress of the UAS mission using the two-screen graphical user interface (GUI) in front of them. During the mission, the UASs would move towards the targets and automatically search the area once within range. Operators were required to respond to events, such as communicating with other operators, updating specific UAS parameters (e.g. altitude), and updating information associated with a target (e.g., location) based upon new information. The mission phase contained three segments, {Block-0, Block-1, Block-2, Block-3} that were designated either of {Easy, Medium, Hard}. The task difficulty was manipulated via the frequency of occurrence of events and the number of new targets added in the segment. The 'Easy' block had events occurring approximately every 75 seconds and 1 new target; the 'Medium' block had events approximately every 45 seconds and 3 new targets; and the 'Hard' block had events approximately every 15 seconds and 4 new targets. The SmartEye system captures eye-tracking at 60 samples/sec while the participant performs tasks of varying difficulty level; each participant completed two approximately twenty minute sessions. Figure 2.4(c) shows the pupil dilation data collected from one participant during different blocks. Statistical analysis of this data (collected from 23 participants) showed some level of success in detecting different levels of cognitive load experienced by participants using pupil diameter measurements [80].

In summary, the experimental data collection designed around a simulated UAS operation showed that the cognitive load experienced by individual while engaging in real-world-like activities can be detected using non-invasive measures, such a pupil



(a) Conceptual unmanned aerial systems (UAS) operation

(b) Measurement set-up from one participant



(c) Pupil diameter during tasks of varying difficulty level [80]

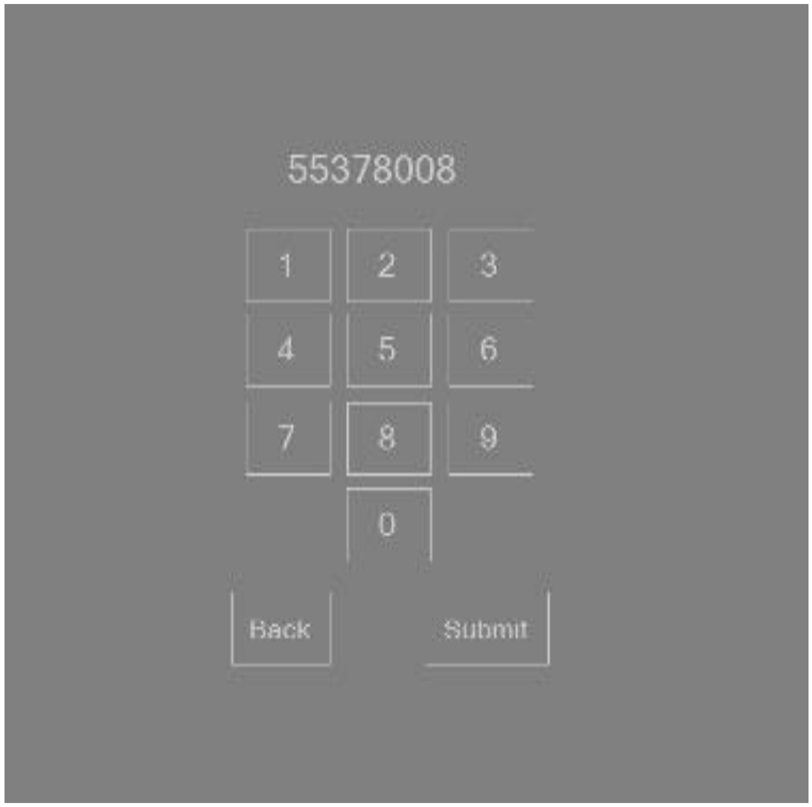
Figure 2.4: **Simulated UAS management task.**

diameter. It must be kept in mind that much more research needs to be done in order to develop a *closed-loop HMS automation* illustrated in 2.1.

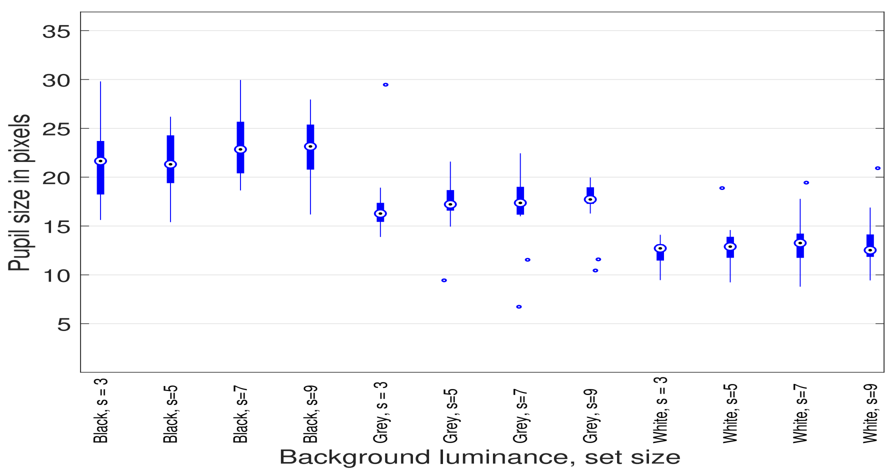
2.3.2 Memory Recall Tasks

Memory recall tasks are useful to emulate tasks requiring varying levels of cognitive load, such as, operating equipment, driving, and learning. Figure 2.5(a) shows the interface used to conduct a digit span experiment in [81]. A brief description of the experimental procedure is as follows: The participant is given digits of sizes 3, 5, 7 and 9 under three different screen luminance conditions (black, gray and white) in audio format; the participants were told to focus on a central fixation cross (a "+" sign $\sim$ 50 pixels tall and wide) that was offset from the background color (80 brighter for the black and gray backgrounds, and 80 darker for the white background) while he/she was listening to the audio. The string of numbers was then sequentially presented at a rate of 1 digit per second. Once the number is given, a numeric keypad, similar to the one shown in Figure 2.5(a), appeared on the screen and participant is asked to use the mouse to input the string of numbers ("2, 6, 1, 8, 4") that they heard by clicking on the corresponding digit in the order they heard. The keypad ensures that participants continued to fixate on the screen while they were making a response; i.e., a verbal response from the participant did not required them to focus on the screen while responding. The keypad had a "back" button allowing the participants to change their response; when satisfied, the participants clicked the submit button.

Figure 2.5(b) shows the pupil diameter (in pixels) measured by the Gazepoint GP3 eye tracker [82]. It was reported in [81] that the pupil diameter had a positive correlation with the difficulty for a given background color. However, the pupil diameter can be seen to be more sensitive to the background color than it is to the cognitive difficulty - this observation underlines the challenges involved in using pupil diameter as a sole indicator of cognitive load. This observation emphasizes the need to study other metrics, such as eye-gaze patterns, eye-blink patterns, hear rate related



(a) Digit-span task interface (grey background)



(b) Pupil dilation at different backgrounds [81]

Figure 2.5: **Digit-span task.** The influence of background color on the pupil diameter is shown.

metrics, all of which can be measured through relatively non-invasive means.

2.3.3 Delayed Memory Recall Tasks

Delayed memory recall tasks or the *n-back task* requires participants to decide whether each stimulus in a sequence matches the one that appeared n items ago. Although n-back has become a standard executive working memory (WM) measure in cognitive neuroscience [83]. N back task has a serial presentation of stimulus in the form of audio spaced few seconds apart and the participant had to repeat out loud number they heard. This task is further classified into 3 stages of increasing difficulty. First one is *zero-back* in this task participant had to repeat same number that they just heard. Next one is called *one-back* where the participant had to repeat one number previous to the number they just heard. Similarly, in the *two-back* task, the participant had to repeat the number they heard two numbers prior. The difficulty of the n-back tasks increase with the delay, i.e., a 2-back task is more cognitively demanding than a 1-back task which is more difficult than a 0-back one. Refer Fig. 2.6 for a sample stimulus (usually delivered in audio format) and the expected response (collected through voice recordings) during 0-back, 1-back and 2-back tasks.

Fig. 2.6(a) shows an experimental setup designed to analyze the pupil diameter in response to n-back tasks of three different difficulty levels. The Gaze point GP3 [82] eye tracker was used to collecting the eye tracking data, response time was collected using detection response task. Entire experiment was divided into two stages: stage 1 had four conditions, and stage 2 had 3 conditions. The participants were asked to look at a '+' sign on the monitor (see Fig. 2.6(a)) during the experiment. The first stage (dual-experiment) of the experiment consisted of 4 conditions namely : Control, 0-back, 1-back and 2-back. Data collected from the participants involved reaction time,Pupil diameter, eye gaze, eye blinks, NASA task load index form and the n-back response. The second stage (single-experiment) of the experiment consisted of 4 conditions namely : 0-back, 1-back and 2-back. Data collected from the participants involved Pupil diameter, eye gaze, eye blinks, NASA task load index form and the n-back response. The mean pupil diameter data collected from 28 participants during the dual-experiment in Figure 2.6; here, an increasing trend can be observed for mean pupil diameter with the n-back difficulty.

2.4 Conclusions and Discussion

This chapter provides some insights into the current progress in human-machine system automation using physiological metrics — particularly pupil diameter — as a measure of cognitive load experienced by humans. Details of four experiments conducted to observe the changes in pupil diameter in response to mental workloads that were simulated to represent realistic human-machine interactive activities were presented in this chapter. The following chapter will discuss one of the experiments described above in detail and some results of the data analysis conducted.

2.5 List of Abbreviations

ADAS Advanced driver assistance systems

DRT . Detection Response Task

ECG . Electrocardiogram

EEG . . Electroencephalogram

EOG . Electrooculogram

ERP . . Event related potential

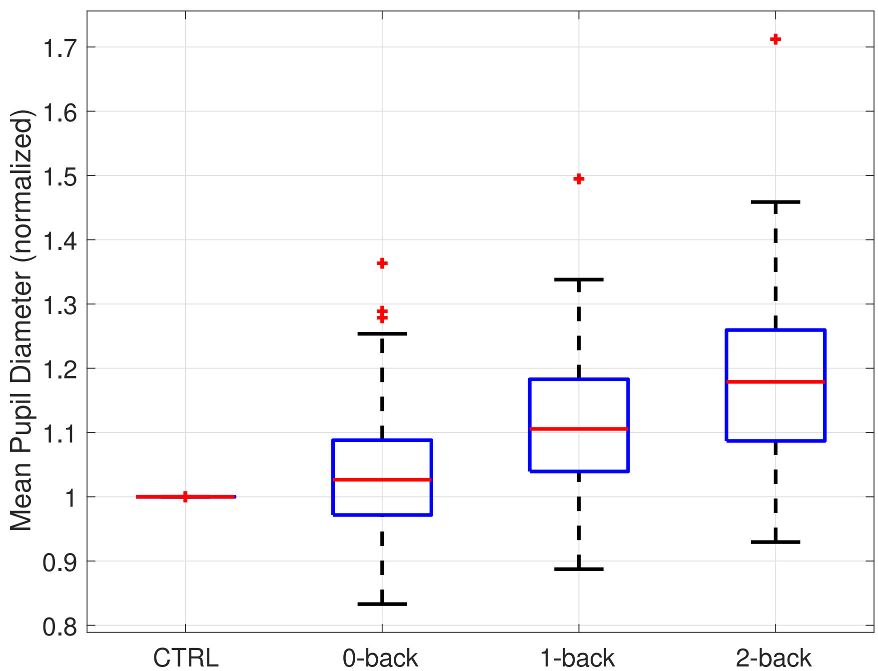
fNIR . Functional near infrared spectroscopy

GA . . . Gaze aversion

(a) Experimental setup

stimulus	0−back	1−back	2−
8	8	-	
7	7	8	
4	4	7	
5	5	4	
2	2	5	
3	3	2	
1	1	3	
9	9	1	
6	6	9	
0	0	6	

(b) Stimulus and expected respons



(c) Box plot

Figure 2.6: **Delayed memory recall task.** Stimulus delivered as an audio play back and the participant is asked to speak the response. The cognitive difficulty increases with the delay.

GP . . . Gaze point

HMS . Human machine system

HR . . . Heart rate

IBI . . . Inter beat interval

MEG . Magnetoencephalography

MOOC Massive online open courses

NASA National Aeronautics and Space Admin.

PET . . Positron emission tomography

QoE . . Quality of experience

TLX . . Task load inde

VoD . . Video on demand

UAS . . Unmanned aerial system

WM . . Working memory

YDL . Yerkes-Dodson law

Table 2.1: **Physiological Metrics of Mental Workload**

Physiological Measurement	**Metrics**
Event-related Brain Potentials (ERPs)	Amplitude and latency of P300 component and Early negativities (first 250 milliseconds) [28]
EEG Activity	Mean power in α(8-13Hz), β (14-25Hz) and θ (4-7Hz) frequency bands of EEG [29]
MEG Activity	Amplitudes of N100m and P200m deflections in the magnetic response to a sensory stimulus, peak latencies of magnetic responses [30]
Brain Metabolism	Regional Cerebral Blood Flow (rCBF)(measured by Positron Emission Tomography (PET), functional Magnetic Resonance Imaging (fMRI)), changes in blood oxygenation in dorsolateral prefrontal cortex (measured by fNIR(functional Near Infrared) spectroscopy) [31]
Pupil Diameter	Average diameter, Maximum pupil dilation [32]
Eye movements	Saccade frequency and saccade distance, Fixation duration, Dwell patterns, NNI, Entropy [33]
Eye blinks (EOG)	Mean blink duration, blink rate and blink latency [34]
Cardiac Activity	Heart rate, Heart beat duration, Heart rate variability, Power in the mid-frequency (0.1Hz component) and high frequency (vagal tone) ranges of the Electrocardiogram (ECG), Interbeat interval (IBI) [35]
Electrodermal Activity	Skin conductance/resistance [36]

Chapter 3

Data Collection Procedure

3.1 Introduction

This section explains in detail the apparatus used for data collection and the process in which the data collection was carried out in detail.

3.1.1 Instructions for the Participants

The following instructions were given to the participants before the beginning of the experiment.

- They are advised to use the restroom as the demonstration can take an hour to complete and no restroom breaks are allowed during the span of the experiment unless the participants has any health issues that need attention.
- They are instructed to keep their original driving license ready for checking by the Principal Investigator.
- This experiment can take an hour to be completed and participants are advised to stay in the laboratory during the entire time of the experiment.
- In case of any doubts or discomfort, participants are advised to contact the PI conducting the experiment.

- They can ask for water during the time inside the lab except when the driving task in underway.

- They are advised to keep their mobile phones on silent (not on vibrate) mode throughout the time when they are in the laboratory and handover all electronic gadgets to the principal investigator to be kept aside.

- They are instructed to remain seated unless they are told otherwise.

- They are told that they can at any time stop the task if they are facing any discomfort but are advised to continue unless the Principal Investigator specifies the end of the driving task.

- They are advised to not break or damage any of the equipment used in the process.

- The equipment attached are safe to be worn and are confirmed that they do not cause any health issues to the participants.

- The participants are required to notify any medical issues/medications that can affect the correctness of the data that is to be obtained.

- All sensors connected will have a trial run for them to be familiarized about its operation.

- They are advised to listen to the instructions carefully and follow as instructed only. They are also informed about the 2-minute breaks in between the demonstrations. They will be asked to relax during this time but are required to remain seated and not remove any of the sensors as they need to be calibrated again if they are removed.

- The participants are supposed to inform any grievances during this break and it will be addressed by the Principal Investigator in the laboratory.

- It is informed that the entire experiment is audio recorded through a microphone placed on the table.
- The entire data from the sensors and the voice file is confidential and is assured that they are used only for research purposes.

3.1.2 Checklist for Principal Investigator

- Print the consent form to be signed by the participant at the start of the experiment.
- Check and maintain cleanliness inside the laboratory.
- Turn ON the PC and check the connections to the sensors: DRT, Driving Simulator, Eye Tracker, and BIOPAC.
- Load and check the N-back audio in the primary laptop.
- Check whether the driving simulator is connected to the PC and responds to external input.
- Assign a specific folder to save the data after end of every experiment.
- Check the connection of PC and devices namely: Microphone, Mouse and Keyboard.
- Ensure all mobile phones are in silent mode and away from the sensory devices.
- Check whether the DRT is working properly: tactile generator and the micro switch.
- Check whether the Eye-tracker is connected and the Gazepoint Analysis software is installed in the PC and responds to the application.
- Charge the laptop in use beforehand. Ensure the BIOPAC is connected as shown in Figure 1.

- Charge the transmitter overnight. Ensure to clean the reusable electrode patches every time.
- Check whether the microphone records audio and create a separate folder for the audio file.
- Check the signal from the ECG and verify its working condition.
- Maintain a backup of all data acquired in the experiment in a separate storage for safety.
- Keep drinking water readily available for the participants.
- The order of the N-back task for the participant is decided using the Latin square technique to counterbalance the experiment.

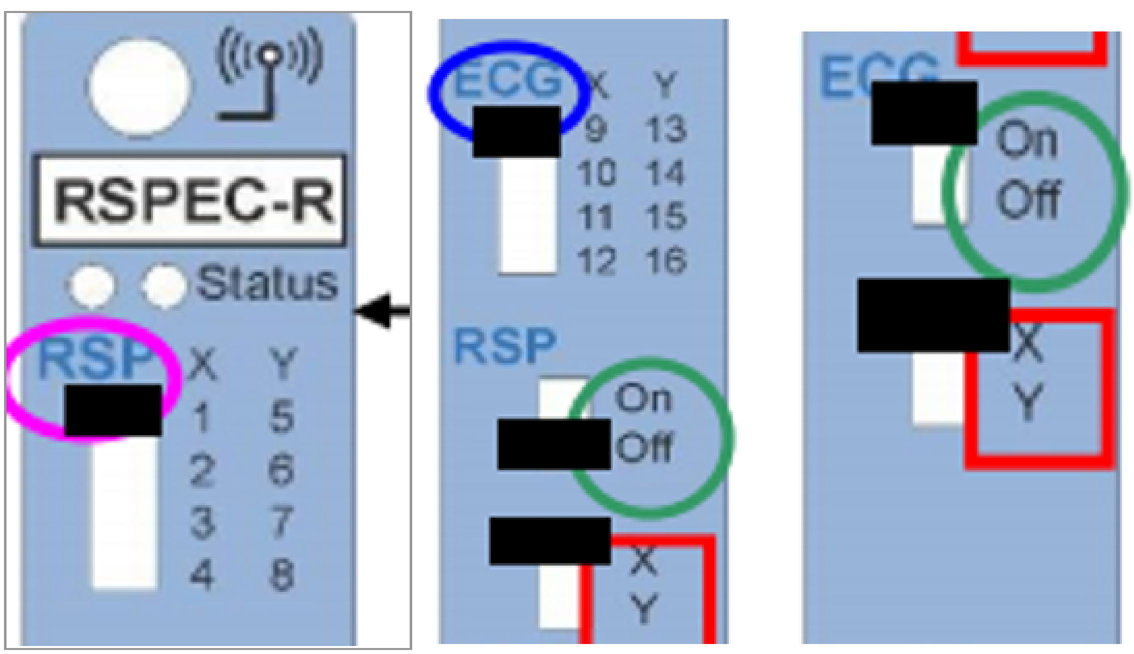


Figure 3.7: **ECG settings.** The above figure shows the options to be setup in the ECG device.

3.1.3 Contingency Plan

The following was the contingency plan during the data collection process for any unexpected incidents that might occur during the process of collecting data. The following questions were asked to the participants by the PI.

- In case of any dizziness from the driving simulator, stop the experiment and exit the Open DS saving files to the extent to which the experiment is completed. Let the participant relax removing all sensors. Open the laboratory door for fresh air and if needed, allow the candidate to have a restroom break. After 10 minutes of relaxation assess the condition of the participant. The condition of the participant was assessed by asking the following questions

- *Do you still experience dizziness or any other discomfort?*

- *Are you suffering a headache?*

- *Would you like to stop the experiment?*

  If the participant answered yes to these questions the experiment would be stopped, and medical attention would be requested if need be.

3.2 Experimental Procedures

Welcome the participant and thank them for being a part of the study when they enter the lab (HK 208). They are then briefed about the experimental procedures with a short description of all the devices being used for data collection. The following was the breifing about the experiment.

The experiment is to study the cognitive load experienced by drivers' based on minimally invasive techniques like DRT to measure your response time to stimuli, Eye tracker for measuring pupil diameter and ECG for measuring heart rate. All this would be measured when driving on a driving simulator and performing N-back tasks. Firstly, I would like you to please read the consent form and sign it. If you have any doubts, please feel free to ask me. There will 3 two minute breaks during the experiment. Please hand over your mobile phones to be kept away during the experiment as we don't want it to cause any interference with the recording devices".

3.2.1 Acquiring Participant details

The Excel file containing the Participant details named as Participantdetails.xls is opened and their Name, Age, Gender, License type, validity, and e-mail ID are taken and populated in the sheet. The file is then saved and the brief introduction of the devices used in the experiment is given to the participants, i.e. the Driving simulator, DRT, Eye-tracker, and ECG.

3.2.2 Driving simulator

The following description about the driving simulator was given to the participants.

"This is a Logitech G29 driving wheel that will be used in the experiment. Please drive on the road and as carefully as possible. Ensure not to go off track and avoid collisions with other vehicles. Please maintain a speed of 70 to 80 km/hr. You are going to be driving on a driving task called the Motorway task all through this experiment. You will encounter 2 turn in the process, please take a right turn whenever you reach this point. You will get there after about 2 minutes."

Participants questions about the driving simulator was answered before moving onto the description of the next device.

3.2.3 Detection Response Task

The following description about the DRT was given to the participants.

"Detection Response Task is a method that is used to obtain values of cognitive load of a task by measuring the response time to stimulus. A tactile generator will be attached near the left forearm and a micro switch is attached to the right index finger. This tactile generator will produce vibrations similar to that of a mobile phone, the micro switch is to be pressed every time you feel a vibration. Be as accurate as possible. Try not to miss pressing the button. When driving and performing this task, please press against the wheel for your own comfort."

Participants questions about the DRT was answered before moving onto the description of the next device.

3.2.4 Eye-tracker

The following description about the Eye Tracker was given to the participants.

"This is a GP3 Gaze point Eye Tracker that would be used for measuring eye-gaze and pupil diameter. Please try not to move your head too much as the eye tracker calibration would be lost if you move away from the range of the eye tracker."

Participants questions about the Eye Tracker was answered before moving onto the description of the next device.

3.2.5 BIOPAC

The following description about the BIOPAC (MP 160) was given to the participants.

"BIOPAC MP 160 is being used to measure the ECG readings. The leads have to be in direct contact with the skin. The belt can be worn on top of your clothes. Adjust the belt so that it is not too loose. The belt and ECG lead positioning sample image is displayed. Please ensure to follow it. 3 electrode patches would be placed on top of the skin, so as to form a triangle around the heart. All the electrode patches are connected with a different colour coded wire to the transmitter."

Any doubts regarding the BIOPAC device is made clear before moving onto the description of the next device.

3.2.6 N-back task

The following description about the N-back task was given to the participants.

"You will hear an audio with asset of numbers. There are 3 different types of N- back task, the 0-back, 1-back and 2-back. The 0 –back task where you have to repeat the number you just heard. The 1 –back task where you have to repeat the number previous to the number you just heard. For the first number you don't have to say anything here. The 2 –back task where you have to repeat 2 numbers previous the number you just heard. For the first 2 numbers you hear, you don't have to say anything. We are using only 0-back and 2-back in this experiment. Now we will move forward with the connection of the devices and their trail runs."

Any doubts regarding the N-back task is made clear before moving onto the description of the next task.

3.2.7 NASA TLX

The following description about the NASA TLX that was given to the participants.

For a measure of the subjective work load that you will experience for every task, you will be asked to fill out a form known as the NASA Task Load Index form. You will fill this after every task. It is a set of 6 questions and you have to rate the level of difficulty based on different parameters- like the physical demand of the task, the temporal demand, and the task difficulty as a whole and so on.Any doubts regarding this task is made clear before moving onto the description of the next device.

3.3 Experimental Setup and Trial Run

3.3.1 ECG Connection

Once the participants have been introduced to the devices used in the experiment, the next step is to begin the connection of the devices. The first of them is the

Figure 8.6

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

Figure 3.8: **NASA TLX Form.**

ECG leads and belt. The participants are instructed to use the alcoholic swabs to clean the area of the skin where the electrode needs to be placed before placing the electrode patches. The ECG leads have to be in direct contact with the skin. A reference picture shown in Fig 3 for the electrode placements is displayed in the lab. Participants are asked to follow the example in picture and place the electrodes as shown: black wire to the right side (on the last rib bone), red wire to the left Side (on the last rib bone), white wire on the right collar bone.

The 3 ECG leads should form a triangle around the heart. The ECG belt has to be worn with adequate tightness just below the chest as shown in the Fig 3, which also shows suggested position for the belt. Once the the ECG device has been worn comfortably, and the wires are not pulling too much from the leads, the PI will ensure correct position of the leads and do a trial run to ensure signals are obtained correctly through Acqknowledge 5.0 software, before proceeding with the connection of the next device.

Next the baseline ECG of the participant is recorded. This is done to record the baseline ECG data that would be used for comparison with the average heart rate later during the experiment. Participants are asked to sit in a relaxed position, looking at the cross on the monitor. The baseline recording takes about 5 minutes. The participant and the PI will not talk to each other during this time and the participants are asked to stay as calm during the course of this experiment.

3.3.2 DRT Connection

Next, the DRT device is attached to the participant: the tactile generator is attached with a medical tape to the left forearm and the micro-switch is attached to the right index finger. The participants are informed about the vibrations that the tactile generator will produce, and they are asked to press the switch that will be attached to their right index finger. The particiapnts are requested to be very accurate. Start the RS Companion App for the trial run of DRT to familiarize the participants with

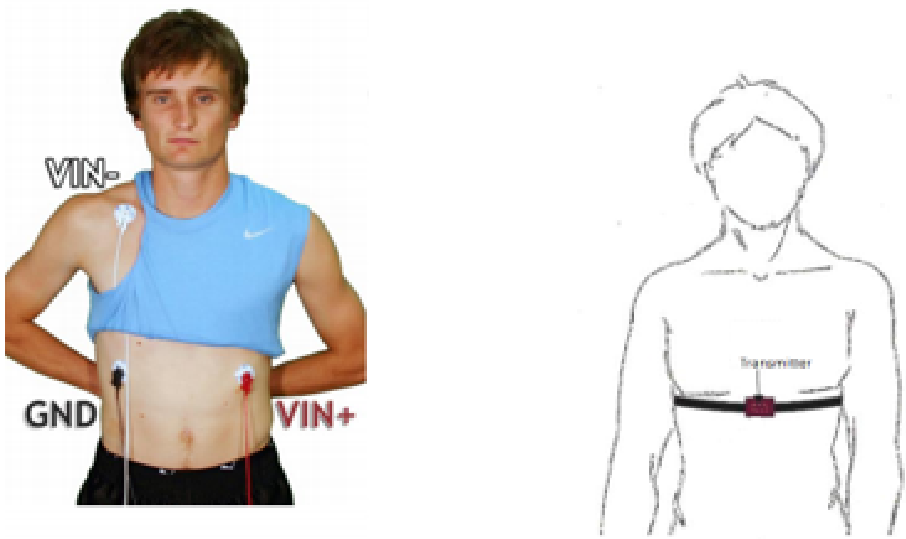


Figure 3.9: **ECG belt position.** The above figure shows the position of the ECG belt.

vibrations that might be produced by the DRT during the course of the experiment. Once the trial for the DRT is over, the next step is to calibrate the eye-tracker and run a trial. The participant is made to sit close to the monitor to aid in calibration.

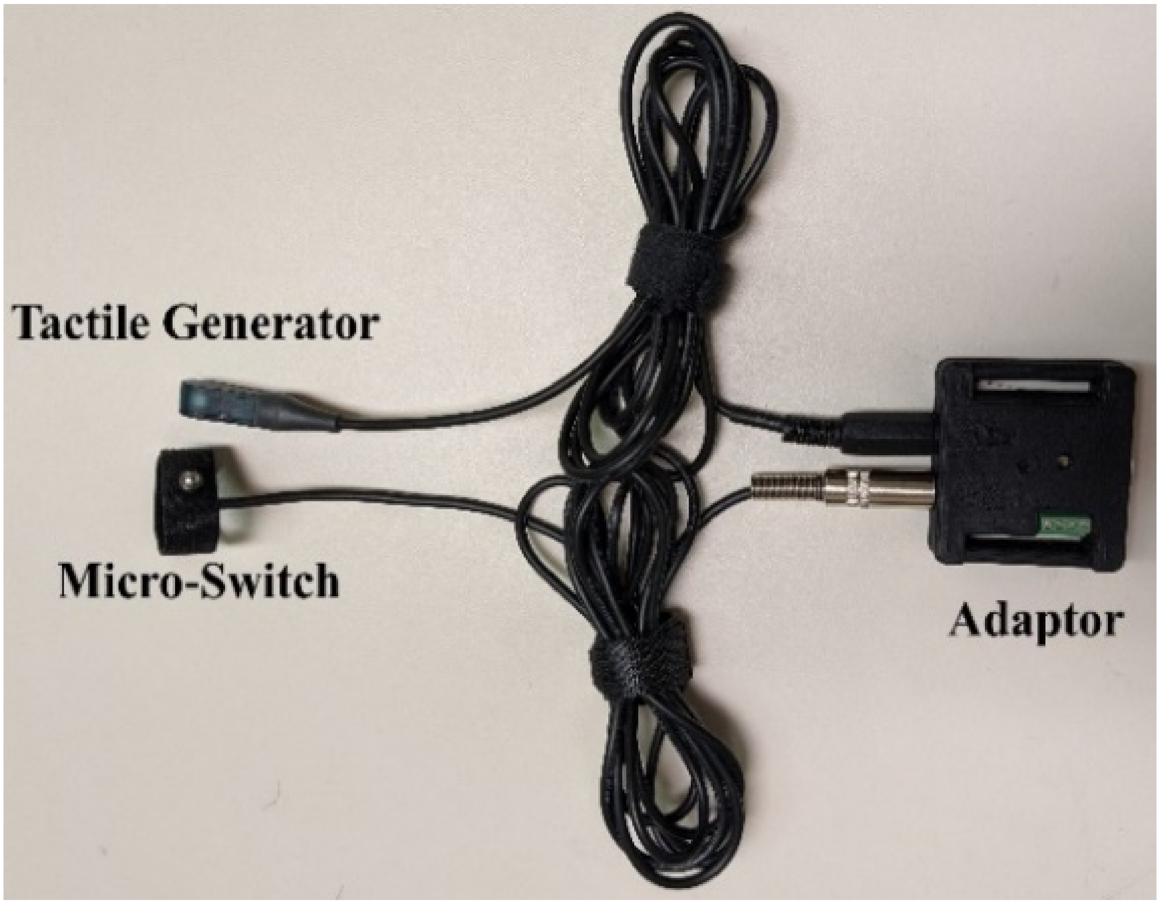


Figure 3.10: **DRT Device.** Detection Response Task recording device

3.3.3 Eye-tracker

The Gaze Point Analysis software is opened to start the calibration process. The 5-point calibration is used for this purpose. The participants are instructed to look at the screen and follow the point on the screen and keep head movements minimal to avoid missed points in the calibration process. Once the calibration is successful, the PI will start recording for 60 seconds to test if the eye-tracker is recording correctly.

Figure 3.11: **Eyetracker.** GP3 Gazepoint Eyetracker

3.3.4 N-back Task

The next trial is for the N-back task. The participants have already been briefed about the N-back task and now a trial audio is played for about 3 to 5 minutes (as long as they get comfortable) for both the 0-back and the 2-back tasks. For the 0-back task, the participants have to simply repeat the number they hear. For the 2-back task, the participants have to repeat 2 numbers previous to the number that was just presented, and for the first 2 numbers presented, no response is expected.

3.3.5 N-back Trial with DRT

In order to better familiarize the participant a trial run for the N-back and the DRT is given together for about 3 minutes.

3.3.6 Driving Simulator Trial

The next trial is for the driving simulator, where the DS Pro App is opened on Motorway task and then Motorway.xml file is opened, the participant is allowed to have a trial run. They are reminded of the speed limit that have been set for the course of the experiment i.e. at 70-80 km/hr along the road. The participants have also been instructed about not to pass the vehicle and not crossover to the other lanes on the road.

The participant to drive for drive for 3-5 minutes and then proceed with the next trial.

3.3.7 Driving Trial with DRT and N-back

The final trial for the participant is driving, DRT with N-back, this is given for the participants to better understand how the experiment will span out.

3.4 Actual Data collection Setup

Now that all trial runs for all the devices have been completed, the data collection process starts here. All devices being used in the experiment have been already calibrated and set-up, any adjustments are made as required. The eye-tracker is calibrated once again before the start of the experiment.

3.4.1 Control Task

For the control task , DS Pro app is opened on the computer with the Motorway task, RS Companion, Gaze Point Analysis and Acqknowledge 5.0 are all restarted. New folders atre assigned and the files are stored seperately. The recording is started on all the following devices is started ECG, eye tracker and DRT. The participants are asked to perform the Control Task while driving on the simulator. Each of the tasks are carried out for a span of 5 minutes and 30 seconds. Once the task is completed, the participants are handed over a tablet which has the NASA TLX form which is a self-rating approach to rate the level of difficulty they faced during this module of the experiment on various parameters (see Fig 2) When they have a short break for 2 minutes, the PI will stop recording from all devices and use this time to save the

Figure 3.12: **Driving Simulator.** Driving simulator to perform the driving task

Figure 3.13: **Experimental Setup.** The Data Collection Setup

DRT, eye tracker and ECG data separately with participant ID in the below format : Participant ID.Taskname.extension.

3.4.2 Zero Back Task

For the 0-Back task , DS Pro app is opened on the computer with the Motorway task, RS Companion, Gaze Point Analysis and Acqknowledge 5.0 are all restarted. New folders atre assigned and the files are stored seperately. Before the zero-back task begins, the microphone is attached to the collar of the participant to record their n-nack audio reponses.

The recording is started on all the following devices is started ECG, eye tracker and DRT. The participants are asked to perform the Control Task while driving on the simulator. Each of the tasks are carried out for a span of 5 minutes and 30 seconds. Once the task is completed, the participants are handed over a tablet which has the NASA TLX form. When they have a short break for 2 minutes, the PI will stop recording from all devices and use this time to save the DRT, eye tracker and ECG data separately with participant ID in the below format : Participant ID.Taskname.extension.

3.4.3 Two Back Task

For the 2-back task , DS Pro app is opened on the computer with the Motorway task, RS Companion, Gaze Point Analysis and Acqknowledge 5.0 are all restarted. New folders atre assigned and the files are stored seperately. Before the zero-back task begins, the microphone is attached to the collar of the participant to record their n-nack audio reponses.

The recording is started on all the following devices is started ECG, eye tracker and DRT. The participants are asked to perform the two back task while driving on the simulator. Each of the tasks are carried out for a span of 5 minutes and 30 seconds. Once the task is completed, the participants are handed over a tablet which has the NASA TLX form. The PI will stop recording from all devices and use this time to save the DRT, eye tracker and ECG data separately with participant ID in the below format : Participant ID.Taskname.extension.

The PI will now recheck that all the data files have been successfully saved is their designated folders. All the sensors are now carefully removed and then the participants are handed over the Tim Hortons gift card and thanked for their participation.

3.5 After the Experiment

The NASA TLX survey is saved in the app and consent form of all participants is documented in a separate file. All 12 sets of data files from all the devices is saved in separate location named after the Participant ID. It is ensured that all devices are turned OFF before removing connecting wires. All connections including the Eye-tracker, DRT and ECG is removed. The ECG belt is cleaned using alcoholic wipes for next use. The transmitter is removed and charged overnight.

Chapter 4

Data Analysis and Introduction to Statistical Analysis

4.1 Introduction

4.1.1 Statistics and its types

Statistics in general is a form of mathematical analysis that uses quantified models, representations and synopses for a given set of experimental data or real-life studies. Statistics studies methodologies to gather, review, analyze and draw conclusions from data. This can be either *descriptive statistics* or *inferential statistics*. For instance, when analysing data, such as the rating for a product by 100 people, it is possible to use both descriptive and inferential statistics in your analysis of the rating they provided. In most research conducted on groups of people, you will use both descriptive and inferential statistics to analyse your results and draw conclusions. Descriptive statistics describes data like a chart or graph and inferential statistics allows you to make predictions or inferences from that data. With inferential statistics, you take data from samples and make generalizations about a population.

4.1.2 Inferential Statistics

The most common methodologies in inferential statistics are hypothesis tests, confidence intervals, and regression analysis. These inferential methods can produce similar values as descriptive statistics, such as the mean and standard deviation. Some types of inferential statistics that are commonly used are listed below.

- Hypothesis test
- Confidence Interval
- Regression Analysis

4.1.3 Student's T-Test

The Student's t-test is used to compare the mean of two populations. The t-test tells you how significant the differences between the means are; in other words, it lets you know if those differences could have happened by chance — with a certain level of confidence. Calculating a t-test requires three key data values. They include the difference between the mean values from each data set (called the mean difference), the standard deviation of each group, and the number of data values of each group. The t-test is used to calculate a t-value that is compared against a critical value obtained from the T-Distribution Table based on the type of test (One-tail test or Two-tail test) .This comparison helps to determine the effect of chance alone on the difference, and whether the difference is outside that chance range. The t-test questions whether the difference between the groups represents a true difference in the study or if it is possibly a meaningless random difference. It is very important to note that T-test can be used to compare only 2 populations, and not more than that. There are 2 hypotheses that is suggested in this that is, the means are same for both the populations under comparison or the means are different. This can be calculated using Excel, Matlab and R Studio. To study the difference between 2 or more populations, Analysis of Variance is used.

4.2 ANOVA

Analysis of variance allows a researcher to examine differences in all population means simultaneously rather than conducting a series of t-tests.

In scenarios where we need to compare the means of more than 2 popluations, assuming 4 different conditions, we may use the appropriate hypothesis test several times, and test C(4,2) or six different null hypotheses. Even though the confidence level is 95%, the confidence of the overall process is less than this because probabilities multiply: 0.95 six times and we get is approximately 0.74, or a 74% level of confidence. Thus the probability of a type I error has increased.

To deal with situations in which multiple comparisons need to be made, ANOVA is used This test allows us to consider the parameters of several populations at once.

4.2.1 Assumptions

There are some assumptions that are made before ANOVA is performed on the data.

Normal distribution: The dependent variable is normally distributed in each group that is being compared in the one-way ANOVA.

Homogeneity of variance: Homogeneity means that the variance among the groups should be approximately equal.

Independence of observations: The sample cases should be independent of each other. This is mostly a study design issue and, the researcher has to determine whether it is possible that the observations are not independent based on their study design.

It is important to understand that the ANOVA is an omnibus test statistic and cannot tell which specific groups were statistically significantly different from each other, only that at least two groups were.

Null hypothesis: The null hypothesis is that there is no difference between the mean of the groups that are under consideration, and all the means are equal.

Alternate hypothesis: The alternative hypothesis is that there is some difference between the mean of the groups that are under consideration. In this case, in order to obtain our p-value, we would utilize a probability distribution known as the F-distribution. There are however many possibilities when the alternate hypothesis is true.

- First : $X1 \neq X2 \neq X3$
- Second : $X1 \neq X2 = X3$
- Third : $X1 = X2 \neq X3$
- Fourth : $X1 = X2 = X3$

Here the 3 groups are X1, X2 and X3. The ANOVA results only shows that the experimental manipulation has had some effect, but it does not help to specifically determine what the effect was. To determine which specific groups differed from each other, a post hoc test must be used.

4.2.2 Types of ANOVA

One Way ANOVA: The one-way analysis of variance (ANOVA) is used to determine whether there are any statistically significant differences between the means of three or more independent (unrelated) groups. The one-way ANOVA compares the means between the groups we are interested in and determines whether any of those means are statistically significantly different from each other. Specifically, it tests the null hypothesis.

Repeated Measures ANOVA: Repeated measures ANOVA is the equivalent of the oneway ANOVA, but for related, not independent groups, and is the extension of the dependent t-test. A repeated measures ANOVA is also referred to as a within-subjects ANOVA or ANOVA for correlated samples. All these names imply the nature of the repeated measures ANOVA, that of a test to detect any overall differences between related means.

The advantage of a repeated measures ANOVA is that whereas within-group variability (SSE) expresses the error variability (MSE) in an independent (between-subjects) ANOVA, a repeated measures ANOVA can further partition this error term, reducing its size.This has the effect of increasing the value of the F-statistic due to the reduction of the denominator and leading to an increase in the power of the test to detect significant differences between means. Mathematically, and as illustrated, we partition the variability attributable to the differences between groups and variability within groups (SSE) exactly as we do in a between-subjects (independent) ANOVA. However, with a repeated measures ANOVA, as we are using the same subjects in each group, we can remove the variability due to the individual differences between subjects, from the within-groups variability (SSE).

4.2.3 F distribution

In probability theory and statistics, the F-distribution, also known as Snedecor's F distribution or the Fisher–Snedecor distribution is a continuous probability distribution that arises frequently as the null distribution of a test statistic. The F distribution is the ratio of two chi-square distributions, U1 and U2 with degrees of freedom d1 and d2 where each chi-square has first been divided by its degrees of freedom.

$$X = \frac{U_1/d_1}{U_2/d_2} \tag{4.1}$$

If a random variable X has an F-distribution with degrees of freedom d1 and d2, we write $X \sim F(d1, d2)$. Then the probability density function (pdf) for X is given by

$$
\begin{aligned}
f\left(x ; d_1, d_2\right) &= \frac{\sqrt{\frac{\left(d_1 x\right)^{d_1} d_2^{d_2}}{\left(d_1 x+d_2\right)^{d_1+d_2}}}}{x \mathrm{B}\left(\frac{d_1}{2}, \frac{d_2}{2}\right)} \\
&= \frac{1}{\mathrm{B}\left(\frac{d_1}{2}, \frac{d_2}{2}\right)}\left(\frac{d_1}{d_2}\right)^{\frac{d_1}{2}} x^{\frac{d_1}{2}-1}\left(1+\frac{d_1}{d_2} x\right)^{-\frac{d_1+d_2}{2}}
\end{aligned} \tag{4.2}
$$

4.3 One Way ANOVA

The one-way ANOVA is used to determine whether there is any statistically significant difference between the mean of three or more independent groups.

4.3.1 Theory

The one-way ANOVA compares the means between the groups we are interested in and determines whether any of those means are statistically significantly different from each other. Specifically, it tests the null hypothesis:

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_k$$

where μ = group mean and k = number of groups.

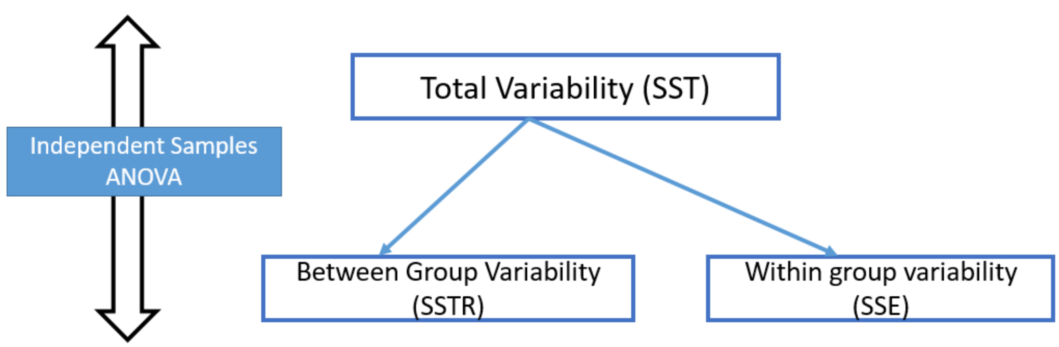


Figure 4.14: **One Way ANOVA.** Logic of One Way ANOVA

4.4 Repeated measures ANOVA

Repeated measures ANOVA is the equivalent of the one-way ANOVA, but for related, not independent groups, and is the extension of the dependent t-test. A repeated measures ANOVA is also referred to as a within-subjects ANOVA or ANOVA for correlated samples. All these names imply the nature of the repeated measures ANOVA, that of a test to detect any overall differences between related means.

- Studies that investigate changes in mean scores over three or more time points, or

- Studies that investigate differences in mean scores under three or more different conditions.

For example, we might get the same subjects to eat taste types of icecream (chocolate, vanilla and strwayberry) and rate each one for taste, rather than having different people taste each different flavors. The important point with this study design is that the same people are being measured more than once on the same dependent variable (i.e., why it is called **repeated measures**), where measurements are made under different conditions, the conditions are the levels (or related groups) of the independent variable called the **within-subjects factor**.

4.4.1 Definitions

- **Total sum of squares(SST)**

  SST is the total variation in the data. It is the sum of the between and within variation given by

$$\text{SST} = \sum_{i=1}^{n}\sum_{j=1}^{c}\left(X_{ij} - \bar{\bar{X}}\right)^2 \tag{4.3}$$

  X_{ij} is the i^{th} observation in the j^{th} column and $\bar{\bar{X}}$ is the grand mean of the

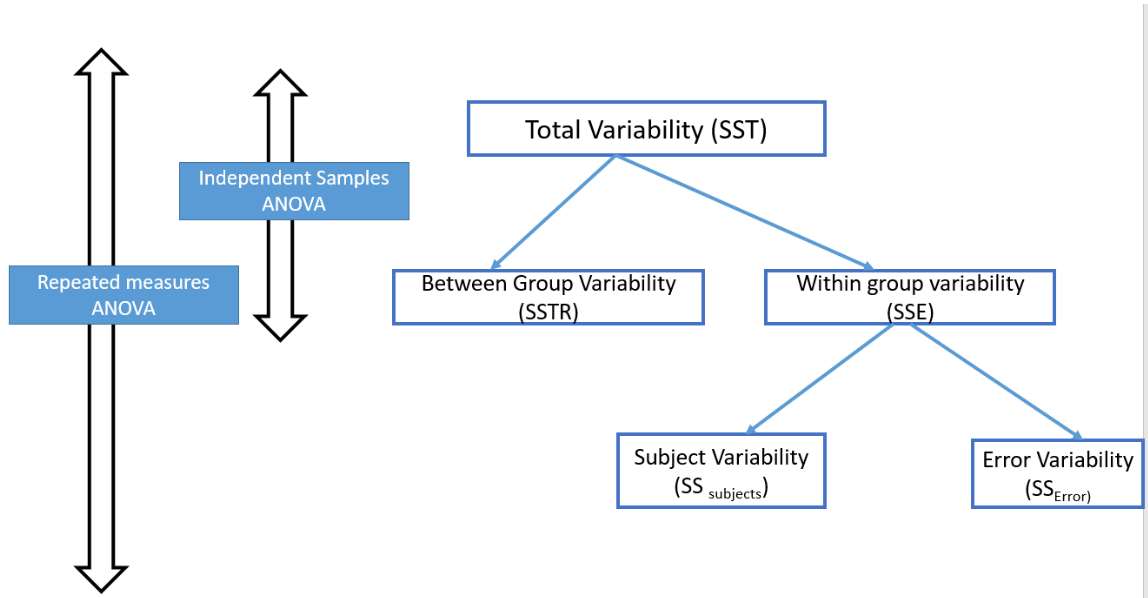


Figure 4.15: **One Way Repeated Measures ANOVA.** Logic of one way Repeated Measures ANOVA design

treatments given by

$$\bar{\bar{X}} = \frac{\sum X_{ij}}{n} \tag{4.4}$$

- **Conditions variability ($SS_{conditions}$)**

  $SS_{conditions}$ is the sum of squares for the differences between related groups. SS_{time} is a more suitable name when dealing with time-course experiments.

$$SS_{conditions} = n \times \sum_{j=1}^{c} \left(\bar{X}_j - \bar{\bar{X}} \right)^2 \tag{4.5}$$

  where $\bar{X}_j$ is the mean of the j^{th} treatment.

- **Within variation (SSE)**

  SSE(or Error Sum of Squares) is the variation in the data from each individual treatment.

$$\text{SSE} = \sum_{i=1}^{n} \sum_{j=1}^{c} (X_{ij} - \bar{X}_j)^2 \tag{4.6}$$

- **Subject variability ($SS_{subjects}$)**

  We treat each subject as a level of an independent factor called subjects and calculate $SS_{subjects}$ as follows:

$$SS_{subjects} = c \times \sum_{i=1}^{n} \left(\bar{X}_i - \bar{\bar{X}}_n \right)^2 \tag{4.7}$$

  where $\bar{X}_i$ is the mean of the i^{th} participant and $\bar{\bar{X}}_n$ is the grand mean of the subjects given by

$$\bar{\bar{X}}_n = \frac{\sum_{i=1}^{n} X_{n1}}{n} \tag{4.8}$$

- Error variability SS_{error}

  The error variability reflects individual variability to each condition in the experiment. It can be also amount to the variance that our model does not account for.

$$SS_{error} = SSE - SS_{subjects} \tag{4.9}$$

- **Mean Squares of Model (MS_{model})**

  Mean Square Model (MS_{model}) is the average subject variability in the data given by the relation:

$$MS_{model} = \frac{SS_{conditions}}{c-1} \tag{4.10}$$

- **Mean Square Error (MS_{error})** Mean Square Error (MS_{error}) is the average variation in the data given by the relation:

$$MS_{error} = \frac{SS_{error}}{(c-1)(n-1)} \tag{4.11}$$

- **F-ratio**

  The F-statistic may now be calculated. For a one-way repeated measures

ANOVA the test statistic is equal to the ratio of MS_{model} and MS_{error}.

$$F = \frac{MS_{model}}{MS_{error}} \tag{4.12}$$

- **Degrees of freedom**

  To find the critical value from an F distribution, the numerator (MS_{model}) and denominator (MS_{error}) degrees of freedom, along with the significance level must be known. F^{CV} has df1 and df2 degrees of freedom, where df1 is the numerator degrees of freedom and df2 is the denominator degrees of freedom, where df1 and df2 are defined as below:

$$df1 = c - 1 \tag{4.13}$$

$$df2 = (c - 1) \times (n - 1) \tag{4.14}$$

  Hence we need to find $F^{CV}_{(df1,df2)}$ corresponding to $\alpha\%$ using the F tables in Appendix 4.16 for the critical value. The null hypothesis is rejected if $F(observedvalue) > F^{CV}$ (critical value).

4.5 Null and Alternate Hypotheses

The null hypothesis is accepted when sphericity is not violated.

Null hypothesis H0: all related group means are equal$\mu_1 = \mu_2 = \mu_3 = \cdot = \mu_k$.. There are no differences between TIME1/CONDITION1, TIME2/CONDITION2, and TIME3/CONDITION3 on the dependent variable. The alternative hypothesis is accepted when the test of sphericity is violated and it is statistically significant i.e. p ¡ 0.05 Alternate Hypothesis HA: at least one related group mean is different .There are differences between TIME1/CONDITION1, TIME2/CONDITION2, and TIME3/CONDITION3 on the dependent variable.

TABLE E

F critical values

Degrees of freedom in the denominator		Degrees of freedom in the numerator								
	p	1	2	3	4	5	6	7	8	9
1	.100	39.86	49.50	53.59	55.83	57.24	58.20	58.91	59.44	59.86
	.050	161.45	199.50	215.71	224.58	230.16	233.99	236.77	238.88	240.54
	.025	647.79	799.50	864.16	899.58	921.85	937.11	948.22	956.66	963.28
	.010	4052.2	4999.5	5403.4	5624.6	5763.6	5859.0	5928.4	5981.1	6022.5
	.001	405284	500000	540379	562500	576405	585937	592873	598144	602284
2	.100	8.53	9.00	9.16	9.24	9.29	9.33	9.35	9.37	9.38
	.050	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38
	.025	38.51	39.00	39.17	39.25	39.30	39.33	39.36	39.37	39.39
	.010	98.50	99.00	99.17	99.25	99.30	99.33	99.36	99.37	99.39
	.001	998.50	999.00	999.17	999.25	999.30	999.33	999.36	999.37	999.39
3	.100	5.54	5.46	5.39	5.34	5.31	5.28	5.27	5.25	5.24
	.050	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81
	.025	17.44	16.04	15.44	15.10	14.88	14.73	14.62	14.54	14.47
	.010	34.12	30.82	29.46	28.71	28.24	27.91	27.67	27.49	27.35
	.001	167.03	148.50	141.11	137.10	134.58	132.85	131.58	130.62	129.86
4	.100	4.54	4.32	4.19	4.11	4.05	4.01	3.98	3.95	3.94
	.050	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00
	.025	12.22	10.65	9.98	9.60	9.36	9.20	9.07	8.98	8.90
	.010	21.20	18.00	16.69	15.98	15.52	15.21	14.98	14.80	14.66
	.001	74.14	61.25	56.18	53.44	51.71	50.53	49.66	49.00	48.47
5	.100	4.06	3.78	3.62	3.52	3.45	3.40	3.37	3.34	3.32
	.050	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77
	.025	10.01	8.43	7.76	7.39	7.15	6.98	6.85	6.76	6.68
	.010	16.26	13.27	12.06	11.39	10.97	10.67	10.46	10.29	10.16
	.001	47.18	37.12	33.20	31.09	29.75	28.83	28.16	27.65	27.24
6	.100	3.78	3.46	3.29	3.18	3.11	3.05	3.01	2.98	2.96
	.050	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10
	.025	8.81	7.26	6.60	6.23	5.99	5.82	5.70	5.60	5.52
	.010	13.75	10.92	9.78	9.15	8.75	8.47	8.26	8.10	7.98
	.001	35.51	27.00	23.70	21.92	20.80	20.03	19.46	19.03	18.69
7	.100	3.59	3.26	3.07	2.96	2.88	2.83	2.78	2.75	2.72
	.050	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68
	.025	8.07	6.54	5.89	5.52	5.29	5.12	4.99	4.90	4.82
	.010	12.25	9.55	8.45	7.85	7.46	7.19	6.99	6.84	6.72
	.001	29.25	21.69	18.77	17.20	16.21	15.52	15.02	14.63	14.33

Figure 4.16: **F distribution table.**

4.5.1 Mauchly's Test for sphericity

Sphericity is the condition where the variances of the differences between all combinations of related measurements are equal. Violation of sphericity is when the variances of the differences between all combinations of related groups are not equal. Mauchly's Test of Sphericity tests the null hypothesis that the variances of the differences are equal.

4.6 Implementation of ANOVA

Statistical tests that are used for 2 groups cannot be used for studying 2 or more groups at the same time. Inorder to compare the mean of all populations simultaneously, Analysis of variance (ANOVA) is used.

4.6.1 Excel

In excel, using the Data Analysis add-in under Data menu, we can perform all statistical analyses to our data. To install the Data Analysis add-in if not already installed, install the *Analysis Toolpak* using the flow given: $File > Options > Add - ins > AnalysisToolPak > Go$. After installing, select the appropriate test in the menu of *Data Analysis* to perform the analysis.

4.6.2 MATLAB

In matlab, the function *anova1* performs one-way ANOVA for any sample data y, grouped by *group* and returns the p-value, tb1 which is the ANOVA table returned as a cell array and stats which can be used to perform the multiple comparison test. The syntax is given as:

Syntax:

[p,tbl,stats] = anova1(y, group)

4.7 ANOVA Interpretation and post hoc

Post hoc tests are an integral part of ANOVA. When you use ANOVA to test the equality of at least three group means, statistically significant results indicate that not all of the group means are equal. However, ANOVA results do not identify which particular differences between pairs of means are significant. Therefore, we use post hoc tests to explore differences between multiple group means while controlling the experiment-wise error rate.

4.7.1 Error Rate

The experiment-wise error rate represents the probability of a type I error (false positive) over the total family of comparisons. For every hypothesis test you perform, there is a type I error rate, which your significance level (alpha) defines. In other words, there is a chance that you will reject a null hypothesis that is actually true—it's a false positive. When you perform only one test, the type I error rate equals your significance level, which is often 5%. However, as you conduct more and more tests, your chance of a false positive increases. If you perform enough tests, you are virtually guaranteed to get a false positive. The error rate for a family of tests is always higher than an individual test.

4.7.2 Types of post hoc tests

- Tukey's Honest Significance Difference (HSD) test
- Bonferroni Procedure
- Fisher Least Significance Difference (LSD)
- Scheffe test

4.7.3 Tukey HSD Test

The Tukey HSD test is a post-hoc test based on the studentized range distribution. The Studentized Range (q) is the difference between the largest and smallest data point in a sample, measured in terms of sample standard deviations. The studentized range distribution is the probability distribution for independent, identically distributed random variables that are normally distributed. It is primarily used in post hoc tests, like Tukey's HSD to limit the Type I error risk. The test compares all possible pairs of means.

4.7.4 Assumption

- Observations are independent within and among groups.
- The groups for each mean in the test are normally distributed.
- There is equal within-group variance across the groups associated with each mean in the test (homogeneity of variance).

4.7.5 Implementation

In excel, in order to perform post hoc tests to ANOVA results, the Real Statistics Resource Pack is required. Press Ctrl + m for the Real Statistics Resource toolbox. In the tabs, click on ANOVA. Select on the type of ANOVA based on the input dataset. In the dialog box that appears select the input range, ANOVA type, follow-up post hoc type, α and output ranges. The results of ANOVA along with posthoc results are obtained in the output range of the excel workbook.

4.7.6 Mauchly's Test and Corrections

- The actual results of the repeated measures ANOVA are presented in the Tests of Within-Subjects Effects table. If the data did not violate the assumption of sphericity, you will not need any corrections (no need to correct if you meet the assumption). However, if sphericity was violated, you need to opt for one of the corrections.

- If the assumption of sphericity was violated, and $\epsilon < 0.75$ you need to the Greenhouse-Geisser correction and if the $\epsilon > 0.75$, the Huyhn-Feldt correction is taken.

- The p-value indicates whether or not the repeated measures ANOVA is statistically significant (i.e., whether at least one mean is statistically significantly different from another mean or not). If p ¡.05, you can reject the null hypothesis and accept the alternative hypothesis that the group means are not equal. If p ¿ .05, you must fail to reject the null hypothesis and conclude that the group means are equal. That is, not all group means are equal; somewhere, at least one group mean is different from another group mean.

- This is all we can conclude from a repeated measures ANOVA

- In order to discover where the group mean differences lie, the post-hoc tests is used. If you found that your repeated measures ANOVA is not statistically significant, this is telling you that all group means are equal.

4.8 Statistical Analysis of Data

The data collection procedures have been explained in detail in the previous chapter, data was collected from a group of 16 participants in a driving simulated environment where they were given tasks with increasing level of difficulty and their physiological data was collected. Before we look at the analysis that was performed on the data, there are a few hypotheses that we are trying to statistically test and find out if they are in concurrence with the previous findings.

We have used the One-way repeated measures ANOVA for analysis of our data to statistically conclude which physiological factors significantly changes with the change in the condition of the experiment.

- Hypothesis 1: Mean response time increases with the increase in n-back difficulty.
- Hypothesis 2: No of missed responses increases with increasing n-back difficulty.
- Hypothesis 3: Mean pupil diameter increases with increase in n-back difficulty.
- Hypothesis 4: The NASA-TLX scales recorded for Mental demand, temporal demand, effort and frustration experienced by the participant's increases with n-back difficulty.
- Hypothesis 5: The n-back accuracy decreased with increase in task difficulty.

4.8.1 Response time

Mean response time increases with the increase in n-back difficulty

When we begin the analysis for the response time data, some response times are filtered and not included for analysis, such as reaction time below 100 ms (also known as a premature response) and above 2500 ms (also known as a un-requested response) were removed during data analysis. Also, the number of misses, where the participant did not press the response button, was not included.

Based on increased response times to stimuli or events in controlled driving experiments, concerns, primarily about distractions during driving, have been raised. The cognitive load repeatedly is seen to increase the response times in artificial tasks such as the Detection Response Task (DRT), the results are comparable to real time response to critical traffic situations is questionable. The response time is measured for 3 different conditions: Control, 0-Back, and 2-Back. The mean response time increases with increasing difficulty.

The Mauchly's test for sphericity yields χ^2: 0.005396769 as the result, this means the assumption of sphericity had been violated, and therefore the degree of freedom is corrected using the Greenhouse Geisser correction which yeilded an ϵ value of 0.6554. We use the GG correction in this case and the results show that there was significant effect of the treatments with $F(1.31, 19.66) = 9.003$ $p= 0.004$. This suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Post hoc Tukey HSD test revealed significant differences between Control (mean 587.7974677, SE 57.769) and 2-Back Task (mean 875.593, SE 70.776) conditions ($p = 0.0005$) but not between control and 0 back, and 0 back and 2 back task where the ($p > 0.05$). The effect size for the analysis between Control and 2-Back task ($d = 1.49$) was found to exceed Cohen's d convention for a large effect ($d = .80$).

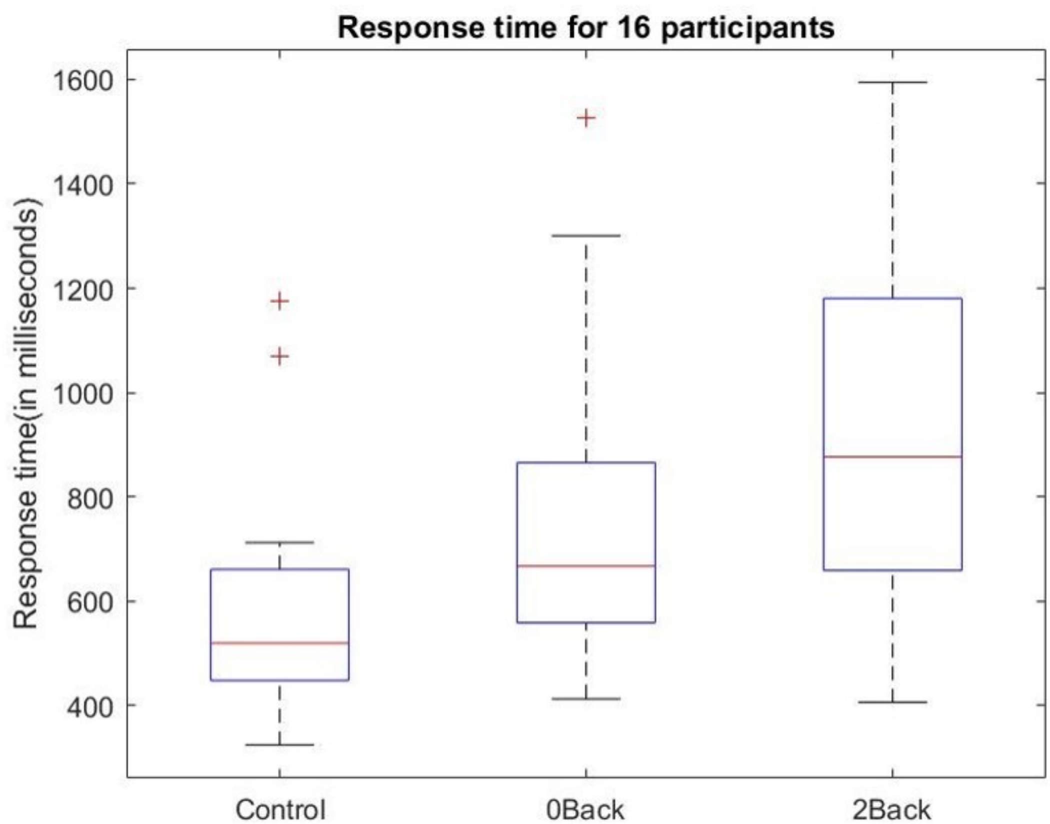


Figure 4.17: **Box plot with response time for all participants.**

The figure 4.17 shows the box plot for the response time for all the 16 participants. The box contains the first and thirs quartile of the

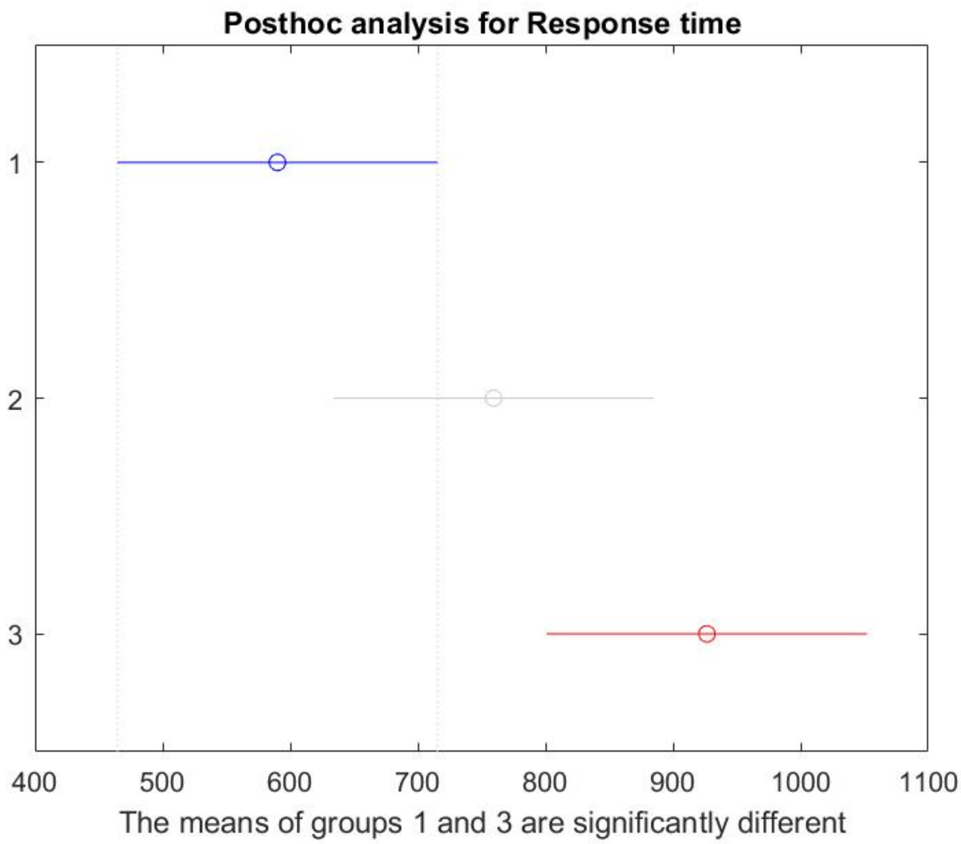


Figure 4.18: **Posthoc for DRT response time in each of the groups.**

From the Fig 4.18 it is clear that the group means of group 1 (Control) is significantly different from that of group 3(2-back). This is in concurrence with the findings from the Excel statistical analysis, but no significant difference was observed with group 2.

4.8.2 DRT missed trials

No of missed responses increases with increasing n-back difficulty

The number of misses by participants increased with the increase in n-back task difficulty. The DRT misses is measured for 3 different conditions: Control, 0-Back, and 2-Back.

The Mauchly's test for sphericity yields: 0.004430827 as the result and the assumption of sphericity had been violated. as the result and the assumption of sphericity had been violated, and therefore the degree of freedom is corrected using the Greenhouse Geisser correction. The ϵ value for Greenhouse Geisser 0.6498 and the ϵ value for Huhyn Feldt 0.6858.) The results show that there was significant effect of the treatments with $F(1.29, 19.49) = 4.880$ p= 0.0031.

This suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Post hoc Tukey HSD test revealed significant differences between Control (mean 4.25, SE 2.56) and 2-Back Task (mean 14.625, SE 3.017) conditions ($p = 0.01$) but not between control and 0 back, and 0 back and 2 back task where the (p ¿ 0.05). The effect size for the analysis between Control and 2-Back task ($d = 1.06$) was found to exceed Cohen's convention for a large effect ($d = .80$).

Based on these results obtained, we see that the q stat value exceeds the q crit value for the case of comparing control and 2-back, which indicates that 2-back is statistically significant with Control but not with 0back. Thus the hypothesis for increase in number of missed trials sigificantly seen between Control and 2-back.

From Fig 4.19 it is clear that the group means of group 1 (Control) is significantly different from that of group 3(2-back). This is in concurrence with the findings from the Excel statistical analysis.

4.8.3 Pupil Diameter

When we begin the analysis for the pupil diameter data, some values times are filtered and not included for analysis, such as PD below 5 pixels and above 30 pixels were removed during data analysis.

The hypothesis being tested is that the mean pupil diameter increased with increase in n-back task difficulty. Mauchly's test indicated that the assumption of

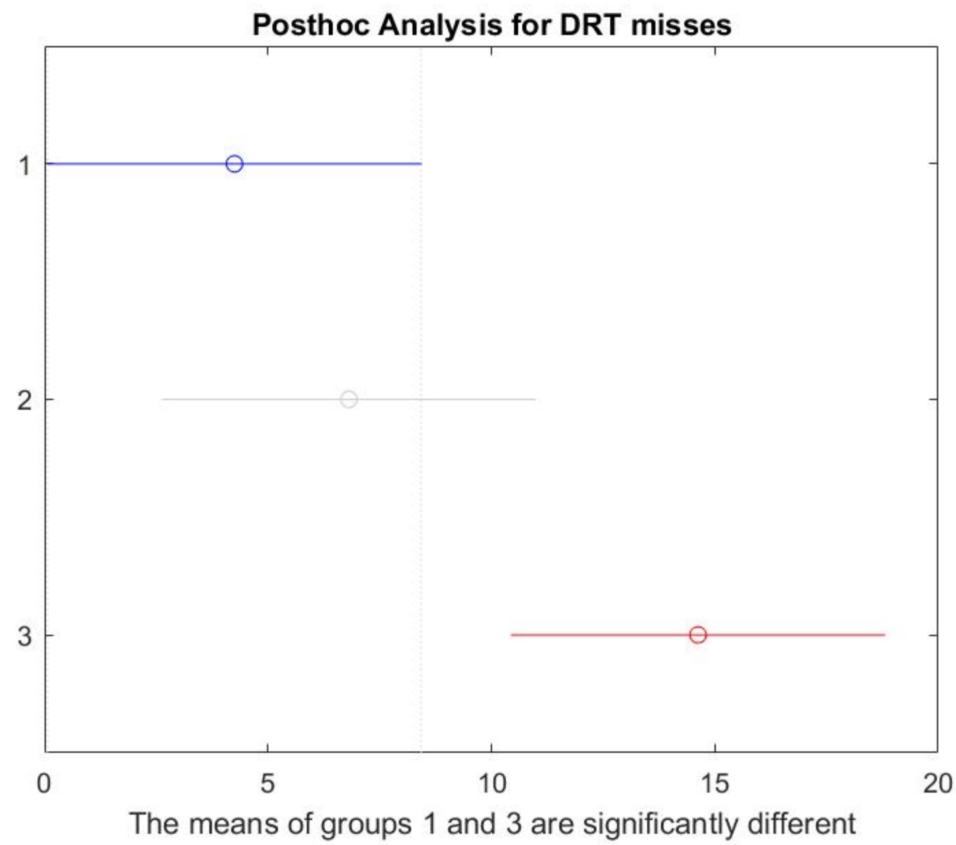


Figure 4.19: **Posthoc for DRT misses in each of the groups.**

sphericity has been violated, p= 0.005397, therefore, degrees of freedom were corrected using the Greenhouse Geisser estimates of sphericity (epsilon = 0.7141). The results show that there was significant effect of the treatments with $F(1.42, 21.42) = 9.9346$, $p = 0.0021$.

Pupil Diameter for all participant is represented as a box plot in the Figure 4.20 for all the 3 conditions. There is a significant increase in the pupil diameter from the control task to the 2-back task which is statistically proven in this section.

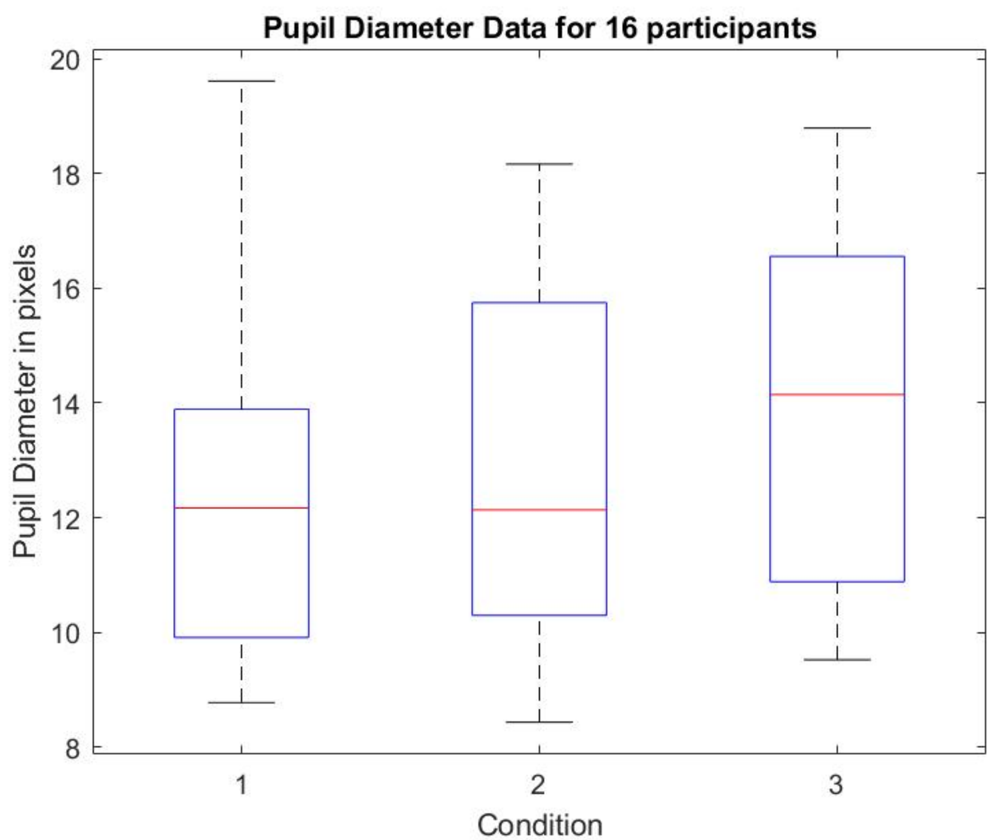


Figure 4.20: **Box plot for all participant pupil diamater.**

This suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Post hoc Tukey HSD test revealed significant differences between Control (mean 12.38, SE 0.7399) and 2-Back Task (mean 13.95, SE 0.8167) conditions ($p = 0.0005$) and also 0-Back (mean 12.81 and SE 0.783) and

2-Back (mean 13.95, SE 0.8167) tasks but not between control and 0 back task where the (p ¿ 0.05). The effect size for the analysis between Control and 2-Back task (d = 1.52) and 0back and 2back (d=1.11) was found to exceed Cohen's convention for a large effect (d = .80).

Based on these results obtained, we see that the q stat value exceeds the q crit value for the case of comparing control and 2-back, which indicates that 2-back is statistically significant with Control and with 0back. Thus the hypothesis for increase in pupil diameter is sigificant seen between 2 conditions: Control and 2-back, 0back and 2-back.

4.8.4 NASA TLX- Analysis of each of the ratings

4.8.5 Mental Demand

The mental demand for the 2-back task is higher than the rating for Control task. To test this hypothesis statistically, first Mauchly's test indicated that the assumption of sphericity has not been violated, p= 0.3678. The results show that there was significant effect of the treatments with F(260.59, 11832.81) = 45.407, p= 0.00001.

Note: When the p value is very small i.e. less than 0.0001, some statistical tools render the value 0.000, the interpretation of such a result is that the results are significant, and below the selected threshold of significance. In this case, it implies high significance.

This suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Post hoc Tukey HSD test revealed significant differences between Control (mean 33.125, SE 5.735) and 2-Back Task (mean 87.187, SE 3.026) conditions (p = 0.0005) and also 0-Back (mean 55.00 and SE 4.6323) and 2-Back (mean 87.187, SE 3.026).The effect size for the analysis between Control and 2-Back task (d = 3.34), 0back and 2back (d=1.99) and control and 0-back (d=1.35) was found to exceed Cohen's convention for a large effect (d = .80).

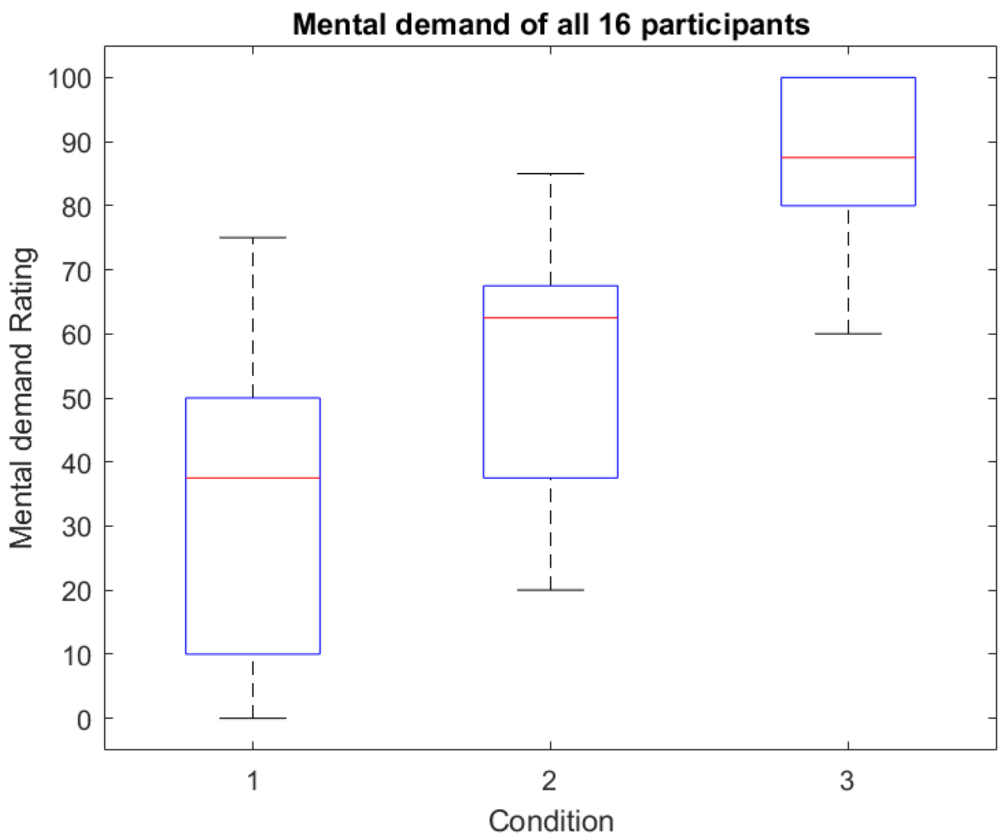


Figure 4.21: **Box plot for Mental demand.**

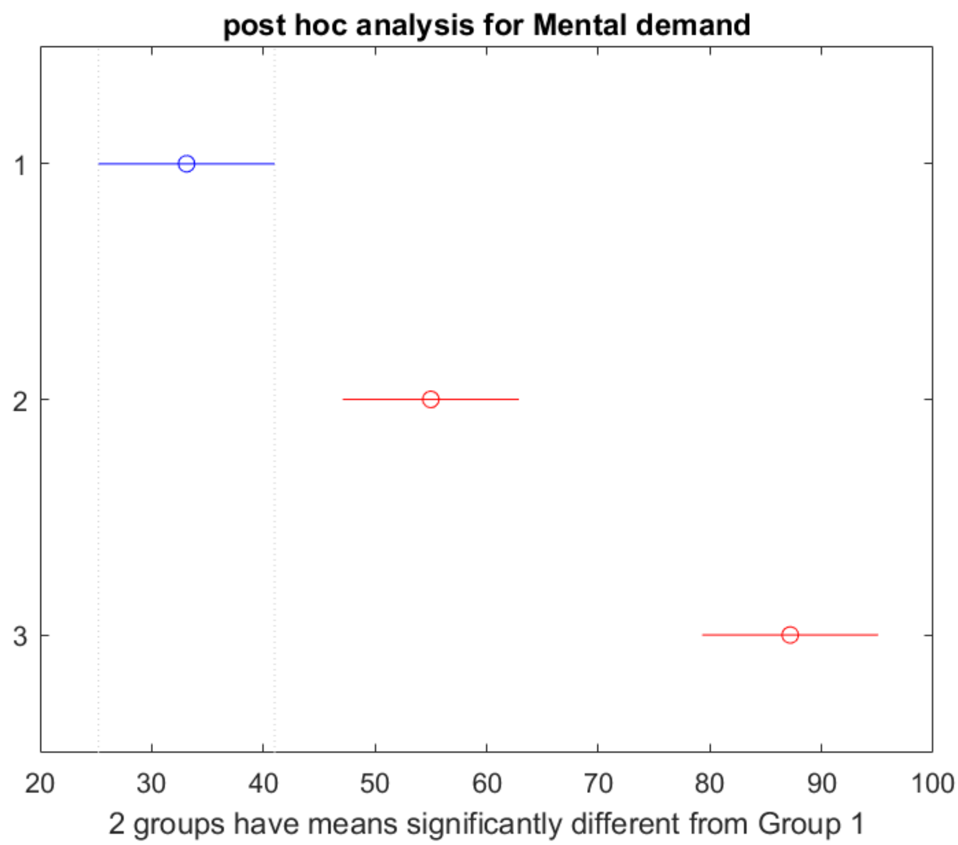


Figure 4.22: **Post hoc plot for Mental demand.**

4.8.6 Temporal Demand

The temporal demand for the 2-back task is higher than the rating for Control task. To test this hypothesis statistically, first Mauchly's test indicated that the assumption of sphericity has not been violated, p= 0.1268. The results show that there was significant effect of the treatments with F(2, 30) = 18.289, p= 0.00006.

This suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Post hoc Tukey HSD test revealed significant differences between Control (mean 28.1250, SE 5.605) and 2-Back Task (mean 69.0625, SE 6.940) conditions (p = 0.0005) and also 0-Back (mean 41.5625 and SE 6.5127) and 2-Back (mean 87.187, SE 3.026)The effect size for the analysis between Control and 2-Back task (d = 2.0971), 0back and 2back (d=1.4087) was found to exceed Cohen's convention for a large effect (d = .80).

4.8.7 Frustration

The frustration level experienced by the participant for the 2-back task is higher than for Control task. To test this hypothesis statistically, first Mauchly's test indicated that the assumption of sphericity has not been violated, p= 0.0812. The results show that there was significant effect of the treatments with F(2, 30) = 24.9723, p= 0.0005.

The post hoc suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Tukey HSD test revealed significant differences between Control (mean 18.750, SE 4.688) and 2-Back Task (mean 61.8750, SE 5.845) conditions (p = 0.000), 0-Back (mean 36.8750 and SE 6.7835) and 2-Back (mean 45, SE 7.6086) and between Contro (mean 18.750, SE 4.688)l and 0-Back (mean 36.8750 and SE 6.7835). The effect size for the analysis between Control and 2-Back task (d = 2.488), Control and 0back (d=1.0457) , and 2Back and 0back (d=1.4424) was found to exceed Cohen's d for a large effect (d = .80).

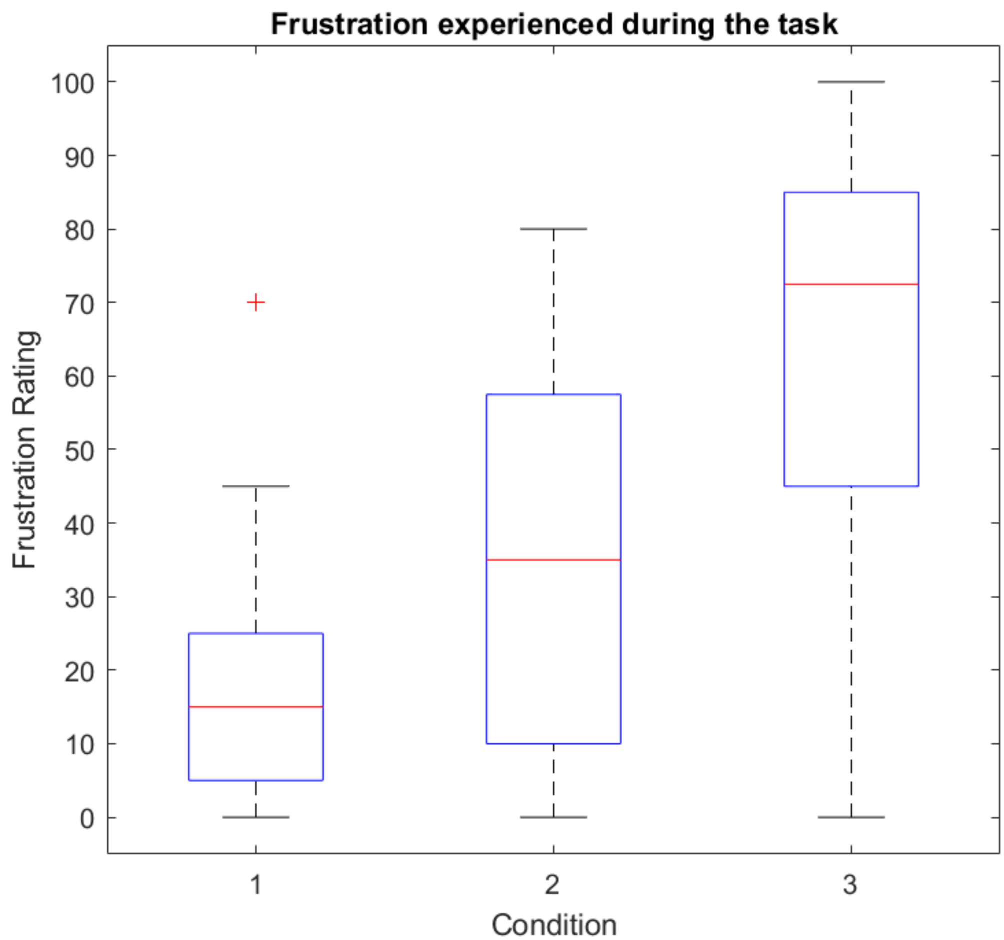


Figure 4.23: **Box plot for frustration taken to acheive the level of performance.**

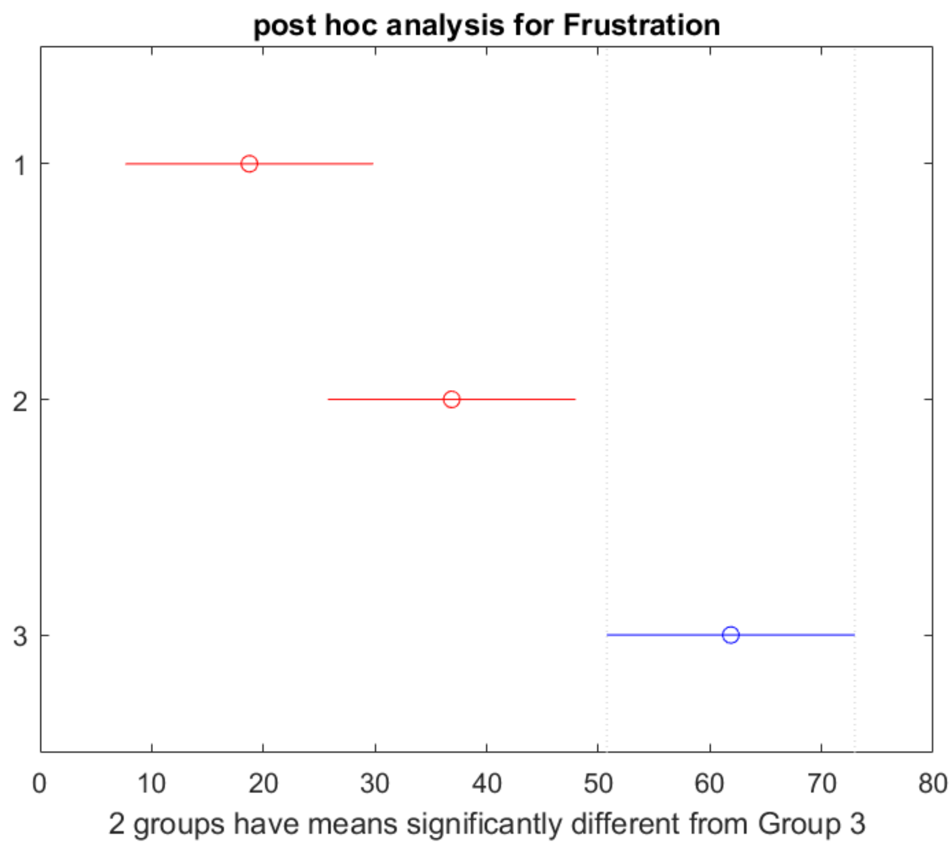


Figure 4.24: **Post hoc plot for frustration level during the experiment.**

4.8.8 Effort

The effort taken to achieve the performance level by the participant for the 2-back task is higher than for Control task. To test this hypothesis statistically, first Mauchly's test indicated that the assumption of sphericity has not violated, p= 0.077. The results show that there was significant effect of the treatments with $F(2, 30) = 14.5918$, p= 0.0004.

The post hoc suggests that there was significant effect observed due to the three treatments namely: Control, 0-Back, and 2-Back. Tukey HSD test revealed significant differences between Control (mean 35.00, SE 6.48) and 2-Back Task (mean 73.75, SE 5.959) conditions ($p = 0.0004$) and between Control (mean 35.00, SE 6.48) and 0-Back (mean 57.812 and SE 3.763). The effect size for the analysis between Control and 2-Back task ($d = 1.90$), Control and 0back (d=1.11) was found to exceed Cohen's d for a large effect ($d = .80$).

4.8.9 N-Back Accuracy

The n-back accuracy decreased with increase in task difficulty

Inorder to analyze the n-back accuracy, we perform the student's t-test and the results from the n-back accuracy indicate that the accuracy reduced with increase in the difficult y of the task. $t(16) = 11.177$, $p = 1.133$. We obtain the results of the test through matlab and h=1, which suggests that the alternate hypothesis is true i.e. the mean n-back accuracy is different for both the groups, here 0-back and 2-back.

As we can see from the Fig 4.28 the accuracy of the n-back response has reduced with an increase in the task difficulty from the 0-back to the 2-back task.

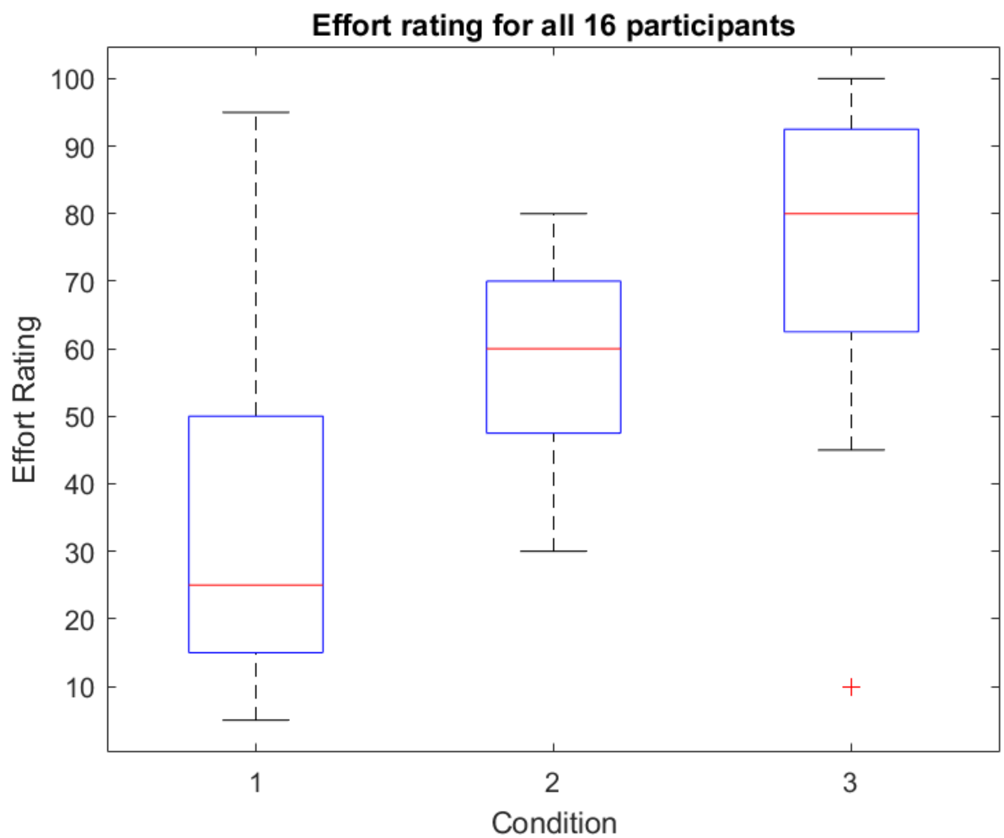


Figure 4.25: **Box plot for effort taken to acheive the level of performance.**

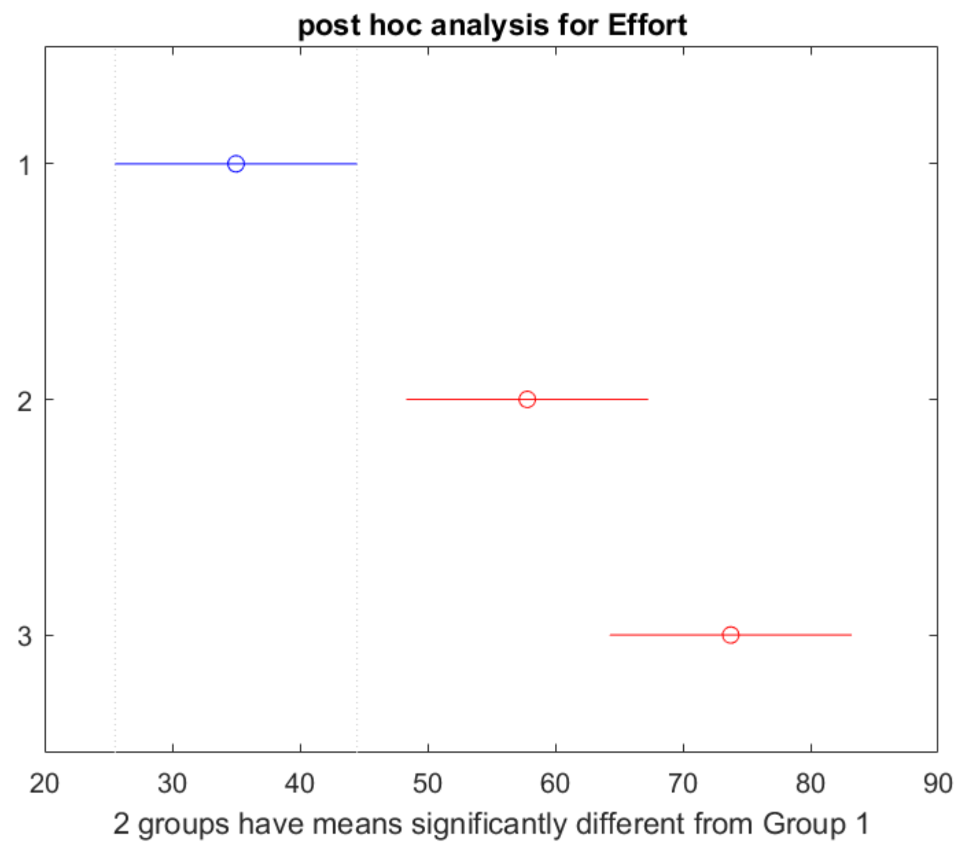


Figure 4.26: **Post hoc plot for effort level during the experiment.**

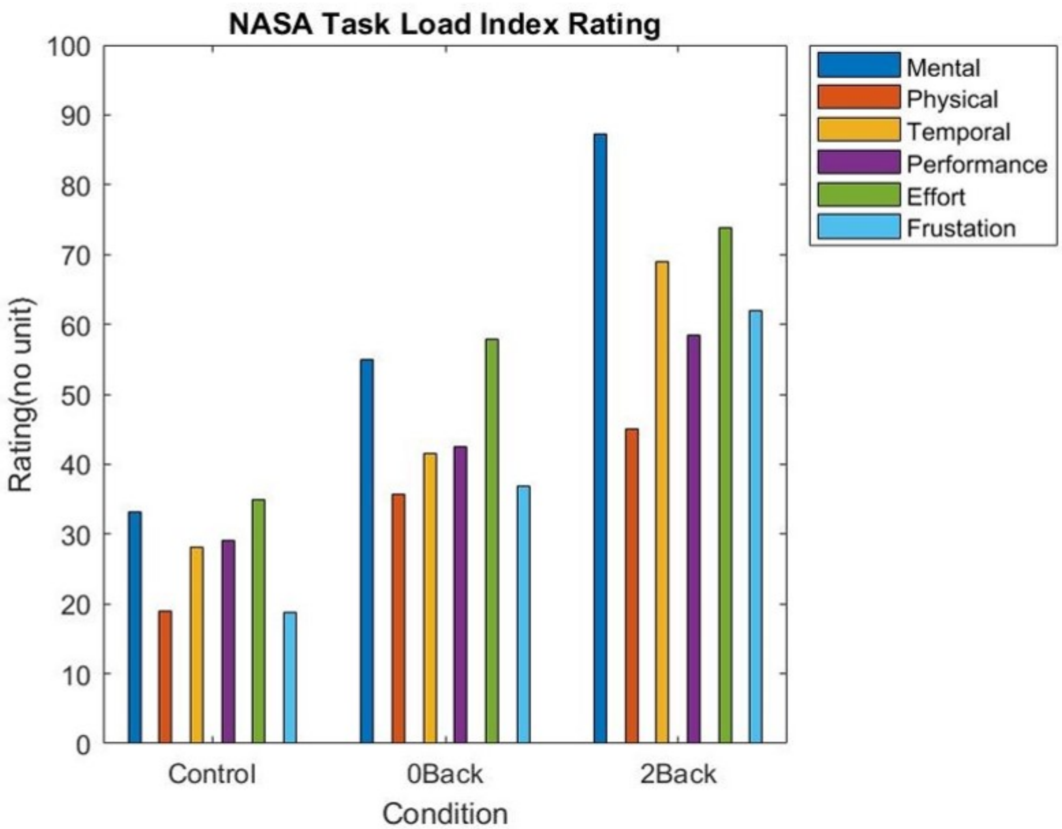


Figure 4.27: **NASA TLX rating for all 16 participants.**

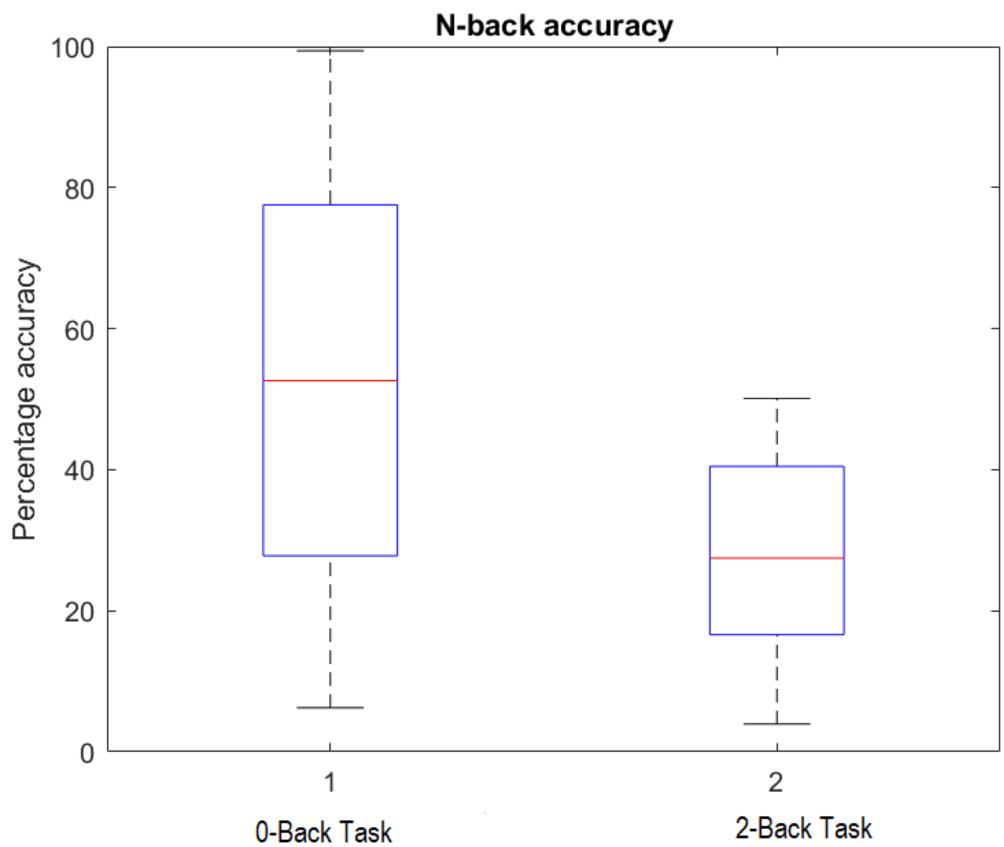


Figure 4.28: **Box plot for n-back accuracy**

Chapter 5

Thesis Conclusion

In summary, the author has presented in this thesis some physiological measures and how they can be indicators of cognitive load. This thesis focuses on cognitive load estimation of drivers when driving on a driving simulator and how the variation of the physiological metrics with increase in cognitive load. The cognitive load variation is presented using the standard n-back tasks.

The author has investigated the feasibility of using pupil dilation as a measure of cognitive load in advanced driver assistance systems (ADAS); as such, a low cost eye-tracker was used to measure the pupil dilation for tasks with varying difficulty. Findings of the pupil dilation coincide with DRT findings for the task 0-back to 2-back and CTRL to 2-back which helps support our purpose of using non-invasive or remote eye tracking (measuring pupil dilation) as a viable solution for detecting cognitive load experienced by an individual. The analysis of NASA-TLX scales indicate that mental demand and frustration imposed by the task on the participant increases with task difficulty.

This study has one limitation: The variation of the surrounding light conditions was kepot constant and hence inorder to better study the pupil diameter as a metric, we need to consider the light variations of the surroundings. However, it is important to point out that many similar studies conducted in a controlled laboratory setting have provided findings that were then replicated in a more realistic environment. Furthermore, cognitive load detection based on pupil dilation has other applications in human-machine system automation, where the findings of this study could be useful.

In terms of future work, the measurement of PD to overcome the known limitations such as: the pupil dilation is affected by other stimuli, such as external light. Other metrics measured through a low cost eye tracker that are also important indicators of cognitive load variation but no deeply investigated in this study are Eye-Gaze and Eye blinks.

One other future work to this study would be to develop a machine learning model to accurately predict cognitive load through pupil dilation. Such a model will exploit the "training data" collected offline to train as such it can be used on new subjects without the requirement for the lengthy training phase.

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